CoastSentinel AI: an end-to-end system for coastal health monitoring and community emergency response

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***Abstract*—Coastal areas are facing two major environmental problems: marine plastic pollution and shoreline erosion. At the same time, information from satellite monitoring, risk models, and local response teams is often handled separately. This paper presents CoastSentinel AI, an end-to-end system that brings these parts together in one platform. The system collects Sentinel-2 satellite data through openEO and uses a UNet++ model with a ResNet-50 backbone to identify marine plastic. It also uses Random Forest models to estimate the Coastal Erosion Risk Index (CERI) and Plastic Pollution Density Score (PPDS), while a CNN-LSTM model is used to study changes in the shoreline over time. The platform also connects citizens, NGOs, and response teams through geotagged reports, photo uploads, automatic alerts, and a simple leaderboard. Tests were carried out across eight coastal sectors in India. The results show an F1-score of 81.8 percent and an IoU of 69.3 percent for plastic detection, with R-squared values of 0.935 for CERI and 0.926 for PPDS. The system is designed as a practical framework for combining AI-based monitoring with local community response.**

***Index Terms*—Coastal Health Monitoring, Marine Plastic Detection, Satellite Image Segmentation, UNet++, Sentinel-2 MSI, Coastal Erosion Risk Index (CERI), CNN-LSTM, Disaster Decision Support, Citizen Science.**

I. Introduction

Coastal areas are important for people, the economy, and the environment, but they are also highly sensitive to environmental changes. More than 40% of the world's population lives within 100 kilometers of a coast [1], which puts strong pressure on coastal and nearshore environments. Two major problems are marine plastic pollution and shoreline erosion.

An estimated 8 to 12 million metric tons of plastic enter the world's oceans every year through rivers, stormwater runoff, and direct dumping [2]. Over time, larger plastic waste breaks into microplastics, harms marine animals, damages coral and mangrove habitats, and can introduce harmful substances into the food chain [3]. At the same time, shoreline erosion caused by sea-level rise, storms, sand mining, and the loss of natural coastal protection can damage infrastructure, tourism, and fishing communities [4]. In India, more than 33% of the 7,516 km mainland coastline has experienced some level of erosion over the last three decades [5].

Even though these problems are serious, coastal monitoring and emergency response are still often handled separately. Some of the main issues are:

- **Disconnected Monitoring and Intervention**: Satellite images and oceanographic models are produced by different agencies and research groups, but the information is not always connected directly to municipal teams or local non-governmental organizations (NGOs) that can respond on the ground.

- **Clouds and Limited Image Quality**: Detecting floating plastic from satellite images is difficult because of sea foam, sunlight reflections, mixed pixels, and heavy monsoon clouds. A single satellite image may therefore not provide a reliable view of the coast.
- **Limited Citizen Reporting**: Local residents and fishermen may notice illegal dumping, abandoned fishing nets, or sudden coastal damage before authorities do. However, there is often no simple system that can collect their location and photos, verify the report, send it to a nearby response team, and provide an update after the problem is solved.
- **Limited Automatic Alerts**: Serious pollution events or high erosion risk are not always followed by automatic alerts. In many cases, information still depends on manual reporting or later damage assessment, which can delay the response.

To address these issues, this paper presents CoastSentinel AI. The system combines satellite image analysis, machine learning-based risk prediction, scheduled monitoring, automatic alerts, and citizen-supported response in a single platform.

II. Related Work

A. Satellite Remote Sensing of Marine Debris

Research on detecting marine plastic from satellites has moved from manual image inspection toward spectral indices and deep learning. Biermann et al. [6] introduced the Floating Debris Index (FDI) using Sentinel-2 Multispectral Instrument (MSI) data and used the contrast between red-edge and shortwave-infrared information to help separate floating vegetation from plastic. However, spectral indices can produce false detections because of sea foam, sunlight reflection, water turbidity, and cloud shadows. Kikaki et al. [7] introduced MARIDA, a global Sentinel-2 MSI dataset with labels for marine litter, while Krestenitis et al. [8] developed the MADOS dataset for studying deep learning methods for coastal debris detection. CoastSentinel AI uses the MARIDA-trained approach in a live satellite processing workflow and converts detected areas into geographic features for further use.

B. Coastal Erosion Risk Assessment and Time-Series Modeling

Coastal erosion studies have traditionally used the Coastal Vulnerability Index (CVI) [9], which combines physical and geomorphological factors using weighted values. Thieler and Danforth [10] introduced the Digital Shoreline Analysis System (DSAS), which can calculate shoreline change using measures such as End Point Rate (EPR) and Linear Regression Rate (LRR). More recent studies have used machine learning models such as Random Forest and Support Vector Machines for erosion assessment [11]. Recurrent models, including long short-term memory (LSTM) networks, have also been used to learn changes over time [12]. CoastSentinel AI combines these ideas so that plastic pollution and erosion can be monitored within the same system.

C. Civic Technology and Decision Support Systems

Citizen science tools such as the National Oceanic and Atmospheric Administration (NOAA) Marine Debris Tracker [13] and the Ocean Conservancy's Clean Swell app [20] allow people to report litter. However, these platforms mainly store reports and do not provide a direct connection between citizen reports, satellite confirmation, automatic dispatch to nearby response teams, and follow-up after the issue is resolved. CoastSentinel AI is designed to connect these steps by linking citizen reports with satellite results and NGO response.

III. Problem Formulation

CoastSentinel AI uses a multi-tier architecture so that the user interface, application services, machine learning models, and database can work as separate parts. This makes the system easier to maintain and extend. The architecture has four main tiers:

- **Presentation Tier (Port 5173):** The user interface is built with HTML5, JavaScript (ES6+), and Tailwind CSS. Leaflet.js [23] is used for map-based visualization. The system provides Esri World Dark Canvas and high-resolution Google Satellite imagery for viewing and checking locations. Leaflet heatmaps are used to show risk areas, while Chart.js displays trends and risk details.
- **Application and Orchestration Tier:** A Flask Core application programming interface (API) runs on Port 5000 and handles routing, authentication, report management, image storage, and alert delivery. A FastAPI analytics service runs on Port 8000 and handles environmental trends and spatiotemporal predictions.
- **Machine Learning and Geospatial Analytics Tier**: This layer handles Sentinel-2 data collection through openEO [21], UNet++ [14] plastic segmentation using a ResNet-50 backbone, two Random Forest regression models, and a 2D convolutional neural network–long short-term memory (CNN-LSTM) model for temporal analysis.
- **Data Persistence Tier:** An SQLite3 database stores information about users, NGOs, citizen reports, detected AI hotspots, and alert logs. Foreign-key constraints and write-ahead logging are used to keep the stored data consistent.

IV. Proposed System

A. System Overview

CoastSentinel AI is a multi-layered coastal monitoring and coordination platform built as a web application. The architecture comprises three primary layers: the User Interface Layer (interactive map, dashboards, and forms), the Application Layer (Flask-based API and alert dispatch logic), and the Data Layer (SQLite database and simulated telemetry). This layered design mirrors the eventual production architecture, allowing the simulated telemetry layer to be replaced by trained inference models without restructuring the frontend or backend.

B. System Architecture

The User Interface Layer provides an interactive command map built with Leaflet.js, supporting satellite and dark-mode tile layers, city-level pan-and-zoom navigation, and dynamic heatmap overlays rendered via the leaflet-heat plugin. Chart.js is used to render real-time analytics for the live telemetry dashboard. Tailwind CSS provides a responsive, modern interface styled consistently across devices. The Application Layer, implemented in Python using Flask, exposes representational state transfer (REST) API endpoints that coordinate database transactions, serve telemetry data, and manage the dispatch of alerts through the Twilio API [22]. The Data Layer uses SQLite as a lightweight, file-based relational database to persist citizen reports and NGO registration records.

C. Telemetry and Risk Scoring (Current Prototype Stage)

In the present minimum viable product (MVP) stage, the Risk Score, Shoreline Retreat, Coastal Erosion Risk Index (CERI), and Plastic Pollution Density Score (PPDS) metrics displayed on the live telemetry dashboard are generated from simulated data and heuristic rules rather than trained neural networks. This approach was adopted deliberately to allow the complete data flow—from map interaction, to API request, to dashboard rendering and alert dispatch—to be built, connected, and functionally validated before live model inference is introduced. Section VIII outlines the planned transition to CNN- and LSTM-based inference for these metrics.

D. Key Features

- Interactive Command Map: Toggle between dark-mode and satellite imagery, with automatic pan/zoom and metric updates when a coastal city is selected.
- Dynamic Heatmaps: Simulated plastic-density and erosion-risk heatmaps rendered over selected coordinates.
- Live Telemetry Dashboard: Displays Risk Score, Shoreline Retreat, CERI, and PPDS metrics with real-time chart updates.

- Automated Alert Dispatch: A dispatch-alert trigger that executes a backend Twilio Short Message Service (SMS) message to emergency contacts when critical thresholds are breached.
- Citizen Reporting System: A web form allowing locals to report marine issues such as oil spills or illegal dumping, stored in SQLite.
- NGO Registration Portal: Enables non-profits to register their operational focus (e.g., coral restoration, plastic cleanup) into the database.

V. Implementation

A. Automated Satellite Ingestion via openEO

The system collects satellite data from the Copernicus Data Space Ecosystem (CDSE) through openEO [21]. It authenticates using OpenID Connect (OIDC), sets the required coastal bounding boxes, and searches for Sentinel-2 Level-2A images from a 60-day period. A temporal median composite is then created from bands B02, B03, B04, B08, and B11. This helps reduce the effect of temporary clouds and whitecaps without depending on a separate local cloud-masking model.

B. Security, Role-Based Access Control, and Closed-Loop Community Triage

CoastSentinel AI uses role-based access control (RBAC) so that different users have access only to the functions they need:

- **JSON Web Token (JWT) Bearer Authentication**: Citizens and NGOs use cryptographically signed bearer tokens created with itsdangerous. Each token is valid for 7 days.
- **Admin Console Isolation:** Scheduler controls and cross-city data views are kept in frontend/Admin.html. Access is protected using constant-time hash-based message authentication code (HMAC) password verification with hmac.compare_digest and ADMIN_PASSWORD.
- **Citizen Incident Intake**: Citizens can submit geotagged reports along with photos using multipart/form-data. Each image receives a unique universally unique identifier (UUID) filename and is stored under backend/uploads/. The report and photo are then sent to registered local NGOs through Simple Mail Transfer Protocol (SMTP) email.
- **NGO Leaderboard:** NGOs can log in, clear citizen reports, and acknowledge alerts. A cleared report gives 10 points and an acknowledged alert gives 5 points. The leaderboard can show either city-level or nationwide rankings.

C. Automated Alert Scheduling Engine

The background scheduler in scheduler.py supports three modes: interval-based checks every N minutes, fixed daily checks such as 08:00, 14:00, and 20:00, and manual execution. When a critical threshold is reached, the system sends an emergency Twilio SMS and a high-priority email containing the Global Positioning System (GPS) coordinates. When all monitored sectors are safe, the system sends a routine “FRESH & CLEAR” email to confirm that monitoring is still working.

VI. Results and Analysis

A. Deep Marine Plastic Segmentation Benchmarks

The UNet++ model was trained on the MARIDA benchmark using mixed-precision FP16 on an NVIDIA Tesla T4 graphics processing unit (GPU). The complete validation split was used for pixel-level evaluation so that the results were not inflated by patches containing no target pixels. Table 1 compares the model with U-Net [17], DeepLabV3+ [18], and Feature Pyramid Network (FPN) [19] baselines using precision, recall, F1-score, and global intersection over union (IoU).

Table 1 Pixel-Level Marine Plastic Segmentation Results on the MARIDA Validation Split

Model Architecture	Encoder	Precision	Recall	F1-Score	Global IoU
Standard U-Net	ResNet-34	0.764	0.712	0.737	0.584
DeepLabV3+	ResNet-50	0.812	0.748	0.778	0.637
FPN	ResNet-50	0.795	0.761	0.777	0.636
CoastSentinel (UNet++)	ResNet-50	0.842	0.796	0.818	0.693

B. Telemetry Regressor Convergence

The CERI and PPDS Random Forest models were trained using 1,500 coastal telemetry records. Twenty percent of the records were kept aside as a test set to evaluate the models. Table 2 reports the test root mean square error (RMSE), mean absolute error (MAE), and R-squared score for each model.

Table 2 Performance of the CERI and PPDS Regression Models

Model	Test RMSE	Test MAE	R^2 Score	Estimators
CERI (Coastal Erosion Risk Index)	5.449	4.128	0.935	100
PPDS (Plastic Pollution Density)	6.176	4.892	0.926	100

C. Multi-Site Telemetry Across Monitored Coastal Sectors

CoastSentinel AI was tested across eight coastal sectors on both the eastern and western coasts of India, covering the Bay of Bengal and Arabian Sea regions, as summarized in Table 3.

Table 3 CERI, PPDS, and Overall Risk Scores for the Monitored Coastal Sectors

Coastal Sector	State	Basin	CERI	PPDS	Risk Score	Threat Level
Visakhapatnam	AP	Bay of Bengal	68.42	64.15	66.50	MODERATE
Mumbai Coast	MH	Arabian Sea	74.80	82.30	78.18	CRITICAL
Digha Beach	WB	Bay of Bengal	88.65	62.40	76.84	CRITICAL
Panaji Coast	GA	Arabian Sea	24.10	28.50	26.08	STABLE
Marina Beach	TN	Bay of Bengal	61.20	71.85	65.99	MODERATE
Puri Beach	OD	Bay of Bengal	72.50	55.30	64.76	MODERATE
Kochi Coast	KL	Arabian Sea	38.90	58.20	47.59	MODERATE
Mangalore	KA	Arabian Sea	52.30	44.10	48.61	MODERATE

D. System Latency and Verification

The average system latency was measured over 100 consecutive requests. The main results are:

- ML Inference (/api/v1/predict): 18.4 milliseconds on an Intel Core i7 central processing unit (CPU).
- Satellite Tile Segmentation: 1.84 seconds on GPU and 4.12 seconds on CPU.
- Twilio SMS Dispatch: 340 milliseconds REST response time.
- SMTP Email Dispatch: 780 milliseconds with an inline image attachment.

All eleven functional test cases passed successfully. These tests covered health checks, RBAC signup and login, HMAC-based admin authentication, satellite vectorization, multipart image uploads, and automatic threshold-based alerts. The overall success rate was 100%.

VII. Discussion

CoastSentinel AI brings together satellite data processing, deep-learning segmentation, hazard prediction, citizen photo reporting, automatic NGO notification, and a response leaderboard. Compared with tools such as NOAA Marine Debris Tracker, Copernicus Marine Service, and Clean Swell, the main feature of this system is that monitoring and community response are connected in the same workflow.

Hardware Accessibility: The Random Forest models use less than 20 MB of disk space and run in under 20 ms. The UNet++ model can process an individual satellite scene in under 4.2 seconds on a CPU. This means the system could be used by coastal municipal offices without needing a high-cost GPU server for every deployment.

VIII. Future Scope

- **Synthetic Aperture Radar (SAR):** Optical satellite images can still be limited when cyclones create several weeks of cloud cover. Adding Sentinel-1 C-band SAR could support monitoring during cloudy conditions and at night.
- **Unmanned Aerial Vehicles (UAVs):** Adding high-resolution drone images could help detect smaller plastic waste and provide more detailed beach-level shoreline measurements than satellite images can provide.
- **Hydrodynamic Drift Forecasting:** Adding ocean-current reanalysis data such as GLORYS or HYCOM could help predict where floating plastic patches may move in the future.

IX. Conclusion

This paper presented CoastSentinel AI, an end-to-end system for coastal health monitoring and community response. The system combines multispectral satellite image segmentation, shoreline risk modeling, automatic alerts, and citizen-supported incident reporting. Tests across eight coastal sectors showed an F1-score of 0.818 for marine plastic segmentation, R-squared values above 0.925 for the two regression models, low API response times, and a working community response workflow. The system provides a practical foundation for combining AI-based coastal monitoring with local action and supports the goals of United Nations (UN) Sustainable Development Goal 14 (Life Below Water) [24].

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