AI-Based Ship Recognition System

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***Abstract*—** Maritime surveillance plays a crucial role in ensuring coastal security, safe navigation, environmental protection, and efficient port operations. Conventional monitoring systems such as radar and Automatic Identification Systems (AIS) suffer from several limitations, including high infrastructure costs, dependency on cooperative vessel behavior, and reduced reliability under adverse weather conditions or deliberate transponder shutdowns. These challenges highlight the need for intelligent, cost-effective, and robust alternative surveillance solutions.

This paper describes an AI-based system for detecting and monitoring ships that uses deep learning and computer vision to find and classify ships in satellite and aerial images. The suggested system uses the YOLOv8 object detection model [2] to find and classify ships in complicated ocean environments with high accuracy. The processing pipeline consists of preprocessing images, extracting features, finding ships, classifying them, and validating the results after processing. The system's performance is measured using standard metrics like Precision, Recall, and mean Average Precision (mAP) in different sea states and lighting conditions.

The system combines geolocation and weather data to make it more useful for operations. This lets it be aware of its surroundings and automatically send alerts when there are dangerous conditions or unusual vessel behavior, like going too fast or losing an AIS signal in restricted maritime areas. We created an interactive web-based dashboard using Streamlit and Folium that shows detected vessels with real aerial ship photos as circular map markers, vessel counts, geographic locations, Mobile Digital Twin positions, and alert notifications in real time.

The proposed system is modular, scalable, and open-source, which means it can easily work with the maritime monitoring systems that are already in place. It is a useful and inexpensive solution for things like monitoring the coast, managing ports, responding to disasters, and keeping an eye on the environment. The AI-based ship recognition framework shows how deep learning, geospatial analytics, and environmental intelligence can be used together to greatly improve maritime situational awareness.

Keywords - Artificial Intelligence, Ship Detection, Maritime Surveillance, YOLOv8, Mobile Digital Twin, FastAPI, Smartphone GPS Tracking, ngrok Tunnel, Vessel Traffic Monitoring, Weather Alert System, Geospatial Mapping, AIS-like Visualization, Marine Safety, Real-Time Monitoring, Haversine Formula, Streamlit Dashboard.

I. Introduction

Surveillance of the seas is an important part of national security, safe navigation, protecting the environment, and running ports smoothly. The rapid growth of global maritime traffic has made it even harder to keep track of ships moving across large areas of the ocean. Radar systems and Automatic Identification Systems (AIS) are two examples of traditional tracking technologies that have been used to keep an eye on ships. But these systems have some big problems that make them less useful. For AIS-based tracking to work, ships need to work together and actively send out their transponder signals [4]. AIS infrastructure can't see vessels that are running with broken or tampered transponders, which are often called "dark vessels." Also, radar systems need a lot of hardware, are prone to signal loss in bad weather, and don't work well for wide-area surveillance.

The field of Artificial Intelligence (AI) and computer vision technology has undergone significant progress since its foundation. The You Only Look Once (YOLO) architectural frameworks demonstrate high performance in satellite and aerial image object detection and classification tasks through their deep learning-based object detection models. The models use advanced visual feature extraction techniques to analyze complicated maritime environments which allow them to accurately determine ship positions despite difficult light conditions and ocean disturbances and different ship sizes [2][3]. The current version of YOLOv8 presents better average precision results and improved small object detection capabilities and faster processing times which make it ideal for use in maritime surveillance systems.[2]

In addition to image-based detection, the growing number of smartphones with high-accuracy GPS sensors offers a new way to track ships at a low cost. Modern mobile browsers have the HTML5 Geolocation API, which lets smartphones continuously collect data on speed, heading, altitude, and geographic coordinates. By using this feature, a mobile device can act as a cheap vessel transponder, sending real-time location information to a monitoring server without needing special AIS hardware.

This paper introduces NaviGuardAI, a holistic AI-driven vessel detection and monitoring system that amalgamates two synergistic tracking modalities. The first modality uses YOLOv8 for deep learning-based ship detection from satellite and aerial images. This lets you find and classify ships in complicated maritime environments. The second mode adds a Mobile Digital Twin framework. In this framework, a smartphone sends live GPS coordinates to a FastAPI backend server through a secure ngrok HTTPS tunnel. The backend uses the Haversine formula to figure out how far away something is and changes the speed from meters per second to knots to show how fast it is moving. A staleness detection mechanism makes sure that only new location data from the last 30 seconds is shown on the dashboard, which keeps the data accurate and the map accurate.

The system has an interactive web-based dashboard made with Streamlit and Folium that shows the positions of vessels in real time using real aerial photos of ships as circular map markers. The dashboard shows real-time Key Performance Indicator (KPI) metrics like the number of vessels, the number of active alerts, the distance to the nearest vessel, and the status of the Mobile Digital Twin connection. An automated alert system keeps an eye on the behavior of vessels and sends out alerts when they go too fast in restricted areas or lose their AIS signal. Integrating weather data gives maritime decision-making a sense of the environment.

The proposed system is modular, scalable, and can be used without specialized AIS infrastructure. It can be used for coastal surveillance, port management, coordinating disaster response, and monitoring the environment. NaviGuardAI shows that an intelligent and cost-effective maritime situational awareness system is possible by bringing together deep learning-based detection, smartphone-based GPS tracking, secure cross-network communication, and interactive geospatial visualization into one platform.

I. LITERATURE SURVEY

Maritime surveillance has become an essential area of research owing to the escalation of global trade, maritime traffic congestion, and coastal security issues. Classic image processing methods like edge detection, background subtraction, threshold segmentation, and morphological operations were very important for traditional ship detection methods [6]. These methods worked well in controlled settings, but they were very sensitive to changes in light, sea clutter, wave interference, and ships of different sizes. When used on real-world satellite and aerial images, the handcrafted feature extraction methods weren't very strong or able to generalize. Because of this, it became clear that we needed automated and smart detection systems.

The development of deep learning technology enabled Convolutional Neural Networks (CNNs) to achieve superior object detection performance in complex environments[3]. The three region-based detectors R-CNN, Fast R-CNN, and Faster R-CNN established region proposals as a method to combine deep feature extraction with their detection capabilities, which resulted in improved remote sensing image detection accuracy [5]. The multi-stage detection systems required extensive computational power, which made them unsuitable for applications that needed to operate in real time. Researchers developed single-stage detection systems, which included YOLO (You Only Look Once) detectors and Single Shot Detector (SSD) systems to solve this problem [2]. The system design of these architectures allowed them to treat object detection as a regression task, which enabled them to achieve real-time speed while preserving their ability to deliver accurate results. The maritime industry widely uses YOLO-based models because they provide fast and efficient capabilities, which include detecting small objects within large satellite and aerial images.

The detection capabilities of YOLO architectures have improved because the latest YOLOv5 and YOLOv8 updates introduced superior feature pyramid networks and advanced bounding box regression methods and enhanced loss function efficiency. The performance of YOLOv8 shows better mean Average Precision (mAP) results and improved detection of small objects, which maritime experts use to track vessels in high-resolution maritime images [2]. Several research studies have successfully applied YOLO-based models for ship detection in both optical and Synthetic Aperture Radar (SAR) imagery [1][3]. The majority of existing studies concentrate on detection accuracy assessment through precision and recall and mAP metrics, which prevents them from developing systems for actual maritime operations.

Navy marine monitoring systems use Automatic Identification System (AIS) technology to track ship movements while they operate their monitoring systems. The system delivers real-time data which includes the vessel's identity and its current speed and heading and geographical position [4]. The AIS-based systems work effectively for vessels that cooperate with the system but they cannot detect ships which operate without using active transponders which people commonly call dark vessels. The main restriction of this system shows that computer vision-based detection needs to work together with alternative geospatial tracking systems which do not require vessel cooperation. Existing research treats detection and tracking as separate problems instead of creating a complete monitoring system which unifies both functions.

Smartphone sensors now serve as a cost-effective solution for tracking vessels which was previously achieved through dedicated hardware transponders. The modern smartphone contains advanced GPS technology and accelerometers and network interfaces which enable it to track and share geographic information throughout the day. The HTML5 Geolocation API enables web-based applications to access device GPS data without requiring dedicated mobile applications or hardware installation. Existing maritime surveillance research has failed to investigate smartphone GPS technology as a replacement for traditional vessel transponders despite its clear operational advantages.

Researchers have studied geospatial visualization methods which use Geographic Information Systems (GIS) to improve maritime situational awareness. The interactive mapping systems enable users to track ship movements through real-time vessel location updates which display their current positions based on latitude and longitude coordinates. The existing systems display contextual information because they lack environmental intelligence as their main operational capacity.

The secure tunneling technology which ngrok provides enables users to expose their locally hosted servers through encrypted HTTPS connections to the public internet. The tunneling mechanisms allow edge devices like smartphones to transmit sensor data in IoT systems through various network types which include 4G and 5G cellular networks to their backend processing servers. The method allows users to deploy real-time tracking systems without needing to set up static IP addresses or port forwarding which makes deployment easier. The existing literature contains minimal research about using secure HTTP tunneling to transmit live maritime GPS data.

Digital Twin technology permits the development of virtual models which maintain perpetual updates through ongoing stream of live sensor information from their respective physical counterparts. Digital Twin systems enable maritime operations to monitor vessel performance and conduct predictive maintenance and navigation simulations. Khalid et al. demonstrated that Digital Twin integration with maritime systems can significantly improve situational awareness and operational decision-making. The current Digital Twin systems which operate in maritime environments depend on high-priced onboard sensor systems and exclusive data processing technologies which create barriers for small businesses and organizations with limited financial resources. The smartphone functions as a Mobile Digital Twin node which transmits real-time GPS data to a backend system that users can access through the cloud, creating a budget-friendly solution which can expand but needs further investigation.

The safety of maritime operations depends on weather conditions which determine both navigational choices and the likelihood of accidents that occur. The combination of high wind speeds and storm conditions together with low visibility results in an increased likelihood of ships colliding and grounding themselves. The existing research shows that meteorological APIs and forecasting systems are accessible yet they have not been successfully connected to AI-based ship detection systems. The majority of ship detection studies focus on demonstrating algorithm efficiency while they fail to include actual environmental conditions and their respective automated alert systems.

The existing literature shows that high-accuracy ship detection models do not meet the needs of operational maritime decision-support systems. Current research mainly seeks to enhance detection metrics through a unified framework which combines multi-vessel monitoring systems with real-time geospatial visualization and smartphone-based GPS tracking and cross-network communication and environmental analysis and automated alert generation systems. The existing AIS-dependent systems do not track dark vessels whereas computer vision approaches show operational deployment challenges because they do not maintain continuous real-time tracking. A complete solution needs a system which integrates deep learning detection together with smartphone sensor fusion and secure tunneling infrastructure and weather-aware alert mechanisms to provide full maritime situational awareness.

The system which has been proposed as NaviGuardAI establishes a connection between YOLOv8 ship detection system and Mobile Digital Twin tracking system and FastAPI backend processing system and ngrok secured cross-network communication system and interactive Folium map visualization system and multi-vessel monitoring system which uses real ship images and system which automatically generates alerts for speed violations and AIS signal anomalies. The system uses computer vision technology together with mobile sensor fusion and geospatial analytics and environmental intelligence to create a complete maritime monitoring system which includes decision support capabilities.

II. PROPOSED SYSTEM

NaviGuardAI system architecture uses a three-part design system which consists of separate modules that operate in defined layers to combine deep learning ship detection systems with smartphone Mobile Digital Twin tracking technology and secure network communication and geospatial visualization tools and environmental intelligence systems for real-time maritime surveillance and decision support. The complete system design processes two types of input data which include permanent satellite images and real-time satellite-based mobile GPS data to produce maritime situational awareness information through multiple processing steps.

The system is composed of the following primary layers:

1. Input Layer

NaviGuardAI accepts two complementary input modalities. The first modality consists of satellite or aerial images containing maritime scenes, obtained from publicly available datasets or direct uploads. Each image may be optionally associated with geolocation metadata such as latitude and longitude to enable contextual spatial analysis. The second modality is a continuous real-time GPS data stream originating from a smartphone browser running the sender.html interface. The smartphone captures geographic coordinates, speed, heading, altitude, and GPS accuracy through the HTML5 Geolocation API using navigator.geolocation.watchPosition(), and transmits this telemetry to the backend server at configurable intervals ranging from one to ten seconds. This dual-input design enables the system to operate in both offline image analysis mode and live vessel tracking mode simultaneously.

2. AI Ship Detection Layer (YOLOv8)

The satellite and aerial image inputs are processed using the YOLOv8 deep learning model, which performs real-time ship detection and classification. This layer extracts hierarchical visual features through a backbone network and predicts the following outputs for each detected vessel:

- Ship bounding boxes
- Confidence scores
- Ship class labels

The model is trained and evaluated using standard performance metrics including Precision, Recall, and mean Average Precision (mAP) to ensure detection accuracy under diverse maritime conditions, varying illumination, and different sea states. Transfer learning from pretrained YOLOv8 weights accelerates convergence and improves generalization on maritime imagery datasets.

3. Communication and Tunneling Layer

This layer, absent in conventional ship detection systems, forms the backbone of the Mobile Digital Twin module. The smartphone browser transmits GPS payload data via HTTP POST requests to the /mobile/location endpoint of the FastAPI backend server. Since the mobile device and the server may operate on different networks — including 4G and 5G cellular infrastructure — a secure ngrok HTTPS tunnel is established to expose the locally hosted backend server at localhost:8000 to a publicly accessible URL. This eliminates the requirement for static IP configuration or port forwarding and enables cross-network GPS data transmission with end-to-end HTTPS encryption.

4. Processing Layer (FastAPI Backend)

The FastAPI backend server, running on Uvicorn ASGI, forms the central processing engine of the system. Upon receiving a GPS payload from the mobile device, the backend performs the following operations:

- **Unit conversion** — Speed values transmitted in metres per second by the browser Geolocation API are converted to nautical knots using the formula: speed (kts) = speed (m/s) × 1.94384.
- **Distance computation** — The Haversine formula computes the great-circle distance between the mobile device's current position and the Chennai AIS

reference station coordinates (13.0827°N, 80.2707°E).

- **In-memory storage** — The validated and processed GPS record is stored in a server-side dictionary (mobile_store) and dynamically injected into the /ships API response, making the mobile device's position available to the Streamlit dashboard alongside static AIS vessel data.

5. Post-Processing and Mapping Layer

The YOLOv8 pipeline detected ship coordinates which combined with live GPS coordinates from the Mobile Digital Twin system to create an interactive geospatial map that uses Folium and OpenStreetMap and OpenSeaMap tile layers for mapping purposes. The five static AIS vessels on the map each display a circular map marker that uses Base64 encoded aerial photographs to create photorealistic vessel identification. The mobile device displays as a separate green pulsing marker with an icon which enables users to differentiate between the current tracking location and the stationary AIS vessels. The system displays vessel names together with their current speed information directly beneath each marker. The dashed polylines connect every vessel to the AIS reference station which helps users understand distance between the two points. The restricted maritime zone displays as a semi-transparent red circle which has a dashed boundary to show navigational areas that require caution.

5. Weather Intelligence Layer

The system retrieves location-based environmental data corresponding to the geographic coordinates of the monitored maritime area. The dashboard sidebar displays key parameters that include temperature and wind speed in knots and wave height and humidity and visibility. The current system uses a static fallback mechanism to provide weather data which shows typical weather conditions for Chennai coastal areas. The next development phase will implement integration with OpenWeatherMap as a live meteorological API which will allow Mobile Digital Twin to retrieve current weather information based on its actual location.

6. Alert Generation Layer

The alert engine monitors vessel behavior against predefined safety thresholds and generates automated notifications for the following conditions:

- **Overspeed violation** — CB Interceptor operating at 22.4 knots within a designated restricted maritime zone triggers a critical speed alert.
- **AIS signal loss** — MV Malabar King experiencing a four-minute AIS transmission gap triggers an AIS gap warning, flagging the vessel for investigation.
- **Mobile Twin status** — The system continuously monitors the freshness of incoming GPS data and reports Mobile Digital Twin connectivity status on the dashboard.

6. Live GPS-Based Ship Movement Simulation

The system's ability to track live movements was tested through the implementation of a GPS simulation module. The researchers used a mobile device as a simulation tool which transmitted real-time geographical data to the monitoring system. The system continuously displayed updated latitude and longitude information as the mobile device moved from one location to another. The method accurately reproduces actual ship movements through its ability to display routes in real time while using weather conditions for alerts and monitoring ship traffic.

7. All processed information is presented through a Streamlit-based web dashboard. The dashboard displays:

- Detected ships and ship count
- Interactive map visualization
- Ship details and metadata
- Live movement simulation
- Weather conditions
- Alert notifications

This layer serves as the primary interface between the system and end users. Finally, all processed information is displayed through the Dashboard Visualization Module, which provides a unified interface for maritime users. The dashboard presents ship locations, vessel details, weather conditions, and real-time alerts, enabling informed decision-making for marine pilots, harbor authorities, and vessel traffic services.

III. METHODOLOGY

The methodology adopted for implementing the system includes the following steps:

- Dataset Collection and preprocessing
  - Collected ship images from publicly available datasets (e.g., Kaggle)
  - Included satellite and aerial images with varying ship sizes and orientations
  - Converted annotations into YOLO format
  - Performed image resizing and normalization
  - Applied data augmentation to improve robustness under different sea and lighting conditions
- Model Selection
  - Selected YOLOv8 object detection model for real-time performance
  - Utilized pretrained weights (transfer learning)
- Model Training
  - Fine-tuned hyperparameters (learning rate, batch size, epochs)
  - Trained model to detect ships with bounding boxes and confidence scores
- Model Evaluation
  - Evaluated using Precision, Recall, and mean Average Precision (mAP)
  - Tested performance under varying environmental conditions
- System Integration

  - Integrated trained model into real-time inference pipeline
  - Applied confidence thresholding and Non-Maximum Suppression (NMS)
  - Extracted ship count from detection results
- Dashboard & Alert Implementation
  - Developed web-based dashboard for visualization
  - Integrated weather API for environmental monitoring
  - Implemented alerts for:
  - Adverse weather conditions
  - Restricted maritime zone violations
  - Maintained detection logs for monitoring and analysis
  -

IV. TOOLS AND TECHNOLOGIES USED

Components	Description
Python	Core programming language.
YOLOv8	Ship detection model
OpenCV	Image preprocessing & visualization
PyTorch	Deep learning framework
Streamlit	Web-based dashboard
Folium	Map visualization
Weather API	Environmental data
JSON / CSV	Metadata storage
FastAPI	RESTful API backend framework
ngrok	Secure HTTPS tunneling service
HTML5	Browser-native API
Wake Lock API	Browser API preventing smartphone screen sleep

V. EXPECTED OUTCOMES/ DELIVERABLES

The project aims to deliver an operational AI maritime ship detection system which can detect ships through satellite and aerial images while providing continuous geospatial tracking and weather-based notification system. The system combines deep learning models with interactive mapping tools and environmental data analysis and a centralized dashboard system to create a complete maritime situational awareness solution

Specifically, the project aims to produce:

- The software prototype operates as a complete system which provides an interactive dashboard to administrators and maritime users for monitoring detected vessels and viewing ship details and analyzing environmental conditions in real time.

- The AI-based ship detection module (YOLOv8) uses satellite and aerial images to detect ships while providing bounding box information and confidence scores, which it uses to show its ability to operate in various maritime environments.

- The system enables operators to monitor and control multiple ships at once by displaying their real-time locations and operational status through a comprehensive visual interface that includes organized ship information including ship type and current speed and operational status and current location data.

- An interactive geospatial visualization system that dynamically plots vessel locations on a map using latitude and longitude coordinates, providing spatial awareness similar to maritime tracking platforms.

- The system includes a weather intelligence integration module which retrieves and displays environmental parameters including wind speed and visibility and general weather conditions based on the current location of the ship.

- An automated alert mechanism that generates safety notifications under adverse weather conditions, assisting marine pilots and port authorities in decision-making.

- A modular and scalable system architecture that allows future integration of AIS data, real-time satellite feeds, predictive analytics, or collision risk assessment models.

- Performance evaluation metrics, including precision, recall, and mean Average Precision (mAP), to validate the effectiveness and reliability of the detection model.

- The integrated web-based dashboard shows detection results together with ship metadata and environmental conditions through its user-friendly visual display. The geospatial mapping module displays vessel positions through latitude and longitude data which functions like AIS-based tracking systems. The weather intelligence module retrieves location-based environmental parameters, including wind speed and visibility, and triggers alerts under unsafe conditions.

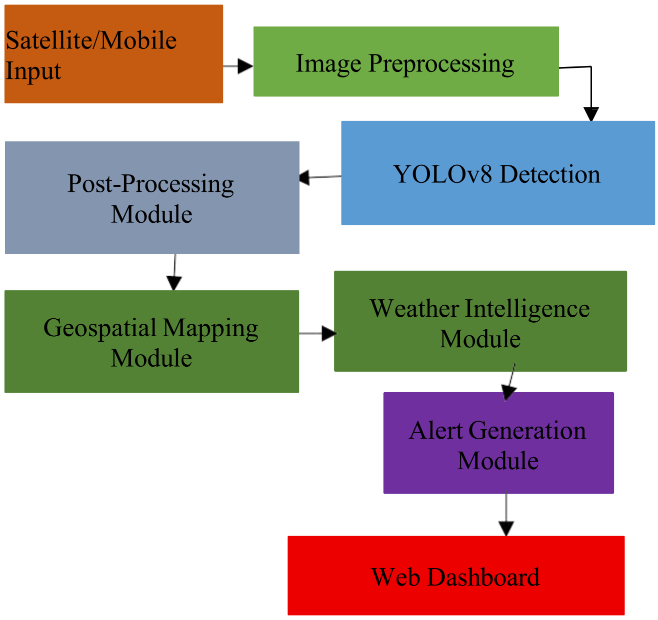
- The testing process for weather-based alert systems used simulated bad weather conditions to verify the system's capability to issue warnings about high wind speeds and low visibility conditions. The alerts provide enhanced situational awareness while showing the system's capacity to assist maritime decision-making during critical safety situations.

- The system demonstrates its ability to operate in actual maritime monitoring situations because it provides near real-time inference capabilities. The system successfully identifies and counts multiple ships that appear in one video frame while tracking their movements. The system uses extracted geographic coordinates to plot vessel positions on an interactive map which enables ongoing monitoring of maritime traffic.

- The researchers conducted a live simulation test which employed a mobile device as a substitute for a moving ship to evaluate system functionality. The system successfully tracked live ship movement data because the device sent GPS coordinates, which showed his position, to the dashboard map for real-time display. The simulation demonstrates that the system can be developed for actual field use and continuous monitoring of ship movements.

- The successful implementation of these deliverables will lead to enhanced maritime monitoring efficiency together with improved navigation safety which will demonstrate the successful integration of computer vision systems and geospatial analytics and environmental intelligence into a complete maritime decision-support system.

VI. System Architecture Flow



VII. Conclusion

NaviGuardAI functions as a complete maritime ship detection system which uses AI technology to improve situational awareness together with operational efficiency and maritime safety.

The system combines deep learning object detection through YOLOv8 with a Mobile Digital Twin tracking system that operates through smartphones and FastAPI backend processing and secure ngrok HTTPS tunnels and interactive geospatial visualization and weather intelligence and automated alert systems to develop a unified and economical maritime decision support system. The framework uses computer vision methods together with mobile sensor combination and geographic analysis and environmental intelligence to achieve maritime monitoring capabilities which exceed traditional detection systems while operating without the need for costly AIS transponder systems.

The implementation shows that deep learning models successfully detect and identify vessels through satellite or aerial images with precise accuracy and instant analysis capabilities. The system combines multi-vessel monitoring with interactive geospatial mapping through Folium to transform raw detection data into spatial insights, which help maritime operators to track vessel movements and monitor their operations. The use of real aerial ship photographs as circular map markers enhances visual identification capability, providing operators with photorealistic vessel recognition directly on the interactive dashboard map.

The Mobile Digital Twin module demonstrates that a standard smartphone can function as a fully operational vessel transponder without requiring dedicated AIS hardware through its successful implementation. The system achieves real-time vessel tracking across heterogeneous networks including 4G and 5G cellular infrastructure by transmitting live GPS coordinates from the smartphone browser to the FastAPI backend through an ngrok HTTPS tunnel. The Haversine-based distance computation and m/s to knots speed conversion together with the 30-second staleness detection mechanism provide accurate and up-to-date information about mobile position data on the dashboard. This approach directly addresses the dark vessel problem identified in the literature survey, offering a practical and deployable alternative to cooperative AIS-based tracking for resource-constrained maritime environments.

The automated alert generation system successfully detects vessel operational violations through its continuous monitoring of vessel operations which it compares to established safety standards. The KPI dashboard bar provides operators with an immediate summary of active alert count, total vessels tracked, moving vessel count, and nearest vessel distance, enabling rapid situational assessment without requiring detailed map inspection. The system gains enhanced operational abilities through its weather intelligence integration which enables safety-critical decision-making by providing environmental data together with vessel tracking information.

Unlike The NaviGuardAI framework together with its advanced detection system and real-time GPS tracking and secure network communication and 3D map rendering and behavior detection and environmental monitoring creates a complete system which can be used in actual situations. The system architecture which uses open-source platforms like FastAPI and Streamlit and Folium and YOLOv8 enables system growth and future system updates. The upcoming project will bring together a weather API which will provide real-time weather information based on the Mobile Digital Twin's current location together with YOLOv8-based visual ship classification which will use camera input and continuous GPS tracking which allows route tracking and assessment and AIS data feed which will support vessel identification and collision danger evaluation which will use vessel movement and heading and distance information.

NaviGuardAI proves that it is possible to create an intelligent maritime situational awareness system which requires minimal hardware resources to connect academic research in computer vision with real-world maritime operations. The system establishes a fundamental technical base which will enable upcoming developments in intelligent maritime surveillance that can be used by multiple users throughout various locations.

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