REAL - TIME OIL SPILL DETECTION
USING AIS AND SATELLITE DATA INTEGRATION

Submitted in partial fulfillment of the requirements for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

Department of CSE-ARTIFICIAL INTELLIGENCE

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DEPARTMENT OF CSE- ARTIFICIAL INTELLIGENCE

KKR & KSR INSTITUTE OF TECHNOLOGY AND SCIENCES
(Autonomous)
(Approved by AICTE New Delhi || Permanently Affiliated to JNTUK, Kakinada) ||
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Vinjanampadu (V), Vatticherukuru (M), Guntur (Dt), A.P-522017.

APRIL – 2025.

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CERTIFICATE

This is to certify that this project report entitled "REAL-TIME OIL SPILL DETECTION USING AIS AND SATELLITE DATA INTEGRATION" submitted by UDAY KIRAN AMBATI (21JR1A4338), NARENDRANATH ATHOTA (21JR1A4340), RAMESH CHIKKALA (21JR1A4354), RAJESH BABU CHILUKA (21JR1A4356), NAGASAI GANGINENI (22JR5A4304) to Jawaharlal Nehru University Kakinada, through KKR & KSR Institute of Technology and Sciences for the award of the Degree of Bachelor of Technology in Department OF CSE-Artificial Intelligence is a bonafide record of project work carried out by him under my supervision during the year 2025.

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EXTERNAL EXAMINER

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DECLARATION

We here by declare that the project **"REAL-TIME OIL SPILL DETECTION USING AIS AND SATELLITE DATA INTEGRATION"** has been carried out by me and this work has been submitted to KKR & KSR Institute of Technology and Sciences (A), Vinjanampadu, affiliated to Jawaharlal Nehru Technological University, Kakinada in partial fulfillment of the requirements for the award of degree of Bachelor of Technology in Department of CSE-Artificial Intelligence.

We further declare that this project work has not been submitted in full or part for the award of any other degree in any other educational institutions.

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PSO2: Computing Paradigms

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PEO:2	Graduates of Computer Science and Engineering - Artificial Intelligence shall have an ability to function effectively in the workplace for professional growth.
PEO:3	Graduates of Computer Science and Engineering shall have exposure to adapt, contribute and innovate new technologies in the key domains of Artificial Intelligence during higher studies or product development.

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1. Engineering knowledge:

Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

2. Problem analysis:

Identify, formulate, research literature, and analyze complex engineering problems reaching substantiated conclusions using the first principles of mathematics, natural sciences, and engineering sciences.

3. Design/development of solutions:

Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for public health and safety, and cultural, societal, and environmental considerations.

4. Conduct investigations of complex problems:

Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

5. Modern tool usage:

Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

6. The engineer and society:

Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

7. Environment and sustainability:

Understand the impact of professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

8. Ethics:

Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

9. Individual and team work:

Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.

10. Communication:

Communicate effectively on complex engineering activities with the engineering community and with society at large, such as being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

11. Project management and finance:

Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.

12. Life-long learning:

Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

Course Outcomes:

S.No.	B. Tech Project CO
CO 1	Interact with customers and identify real world problem statement / identify problems in engineering and technology in selected field of interest.
CO 2	Synthesize and apply prior knowledge of mathematics, computer science and engineering to design and implement solutions to open-ended problems.
CO 3	Design and Develop the software with Software Engineering practices and standards.
CO 4	Use different tools for communication, design, implementation, testing and report writing.
CO 5	Analyzing professional issues, including ethical, legal and security issues, related to software project.
CO 6	Develop better interpersonal communication skills, team work and leadership qualities with writing and oral presentation skills.

Course Outcomes - Program Outcomes mapping

	PO 1	**PO 2**	**PO 3**	**PO 4**	**PO 5**	**PO 6**	**PO 7**	**PO 8**	**PO 9**	**PO 10**	**PO 11**	**PO 12**	**PSO 1**	**PSO 2**
CO421.1	1	2							1	3				2
CO421.2	2	2	1	3								1		3
CO421.3			2		2	3	1	1					3	
CO421.4				1	3	2	2			2	1		2	
CO421.5						1	2	3						
CO421.6									3	1	2	2		
Average	1.5	2	1.5	2	2.5	2	1.6	2	2	2	1.5	1.5	2.5	2.5

ABSTRACT

Oil spills pose severe threats to marine ecosystems, biodiversity, and coastal economies, often resulting in long-term environmental degradation and economic losses. The project titled "Real-Time Oil Spill Detection Using AIS and Satellite Data Integration" presents a comprehensive framework designed to enhance oil spill detection and monitoring capabilities. By leveraging Automatic Identification System (AIS) data for real-time vessel tracking and integrating it with high-resolution satellite imagery, the project enables efficient identification of potential oil spills. AIS data is preprocessed to eliminate noise and inconsistencies, ensuring accurate vessel movement records. Machine learning algorithms are applied to detect abnormal vessel behavior, such as abrupt speed reductions or erratic navigation, which may indicate illegal discharges or maritime accidents. In parallel, satellite imagery is processed using advanced image analysis techniques, including segmentation and classification, to pinpoint suspicious surface patterns.

The integration of AIS and satellite data significantly improves the accuracy, speed, and reliability of oil spill detection. Custom-trained machine learning models help distinguish true oil spills from visually similar phenomena like algal blooms or sediment clouds, reducing false positives. The system not only provides real-time alerts but also helps correlate detected spills with nearby vessel activities, thereby identifying potential culprits and supporting enforcement actions. The findings emphasize the framework's effectiveness in accelerating response efforts, improving containment strategies, and enhancing accountability. Moreover, the scalable nature of the system allows for integration with meteorological data to predict spill trajectories and support clean-up operations. While challenges such as low satellite resolution, AIS signal gaps, and environmental noise persist, the project demonstrates strong potential for operational deployment. Future improvements will focus on refining the processing pipeline, developing intuitive user interfaces for authorities, and incorporating AI-driven predictive analytics to further optimize the detection and mitigation process.

Keywords*:* Oil spill detection, Satellite imagery, Automatic identification system, UNet, DeepLabV3+, Hybrid model, Remote sensing, Deep learning mode

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List of Abbreviations

CNN	Convolutional Neural Networks
SAR	Synthetic Aperture Radar
UML	Unified Modeling Language
UNET	U-Net (a type of CNN architecture for segmentation)

CHAPTER-1: INTRODUCTION

1.1 INTRODUCTION OF THE PROJECT

Oil spills are among the most severe environmental disasters, posing significant threats to marine ecosystems, wildlife, and the economic well-being of coastal communities. These incidents often result from vessel collisions, offshore drilling accidents, or illegal waste discharges. Traditional detection methods like manual inspections and radar surveillance face challenges such as delayed response times and high false alarm rates due to changing weather and sea conditions. Addressing these limitations, the proposed system integrates Automatic Identification System (AIS) data with high-resolution satellite imagery to detect oil spills in real time. AIS data provides vessel tracking insights, while satellite images captured through SAR and optical sensors identify oil slicks even under adverse weather. The system links vessel behavior with spill occurrences, enabling quicker identification of responsible ships and supporting regulatory enforcement.

At the heart of this approach is a hybrid AI model combining UNET and DeepLabV3+ architectures for precise segmentation and feature extraction. This allows accurate identification of oil spills while minimizing false detections caused by look-alike phenomena such as algal blooms or sediment patterns. The system processes large volumes of data in real time, flagging vessel anomalies and supporting early spill detection. Unlike traditional manual methods, this automated framework improves response time, enhances accountability, and provides a scalable solution for environmental monitoring. Future developments will focus on integrating weather-based spill trajectory predictions and deploying a user-friendly dashboard to help authorities monitor and act on incidents more effectively.

1.2 ABOUT THE ALGORITHM

UNET Algorithm

UNET is a deep learning-based convolutional neural network architecture primarily designed for image segmentation tasks. Originally introduced for biomedical image analysis, it has proven to be remarkably effective in domains where precise localization is essential such as environmental monitoring using satellite imagery. The architecture of UNET is symmetric and follows an encoder-decoder structure. The encoder performs feature extraction through a series of convolutional and max-pooling layers, progressively reducing the spatial dimensions while capturing semantic information. Conversely, the decoder reconstructs the segmentation map using transposed convolutions, effectively upsampling the feature maps to the original input size.

What makes UNET particularly powerful is its skip connections that directly link the encoder and decoder layers at corresponding levels. These connections ensure that spatial details lost during downsampling are preserved during upsampling, resulting in highly accurate segmentation boundaries. This is especially valuable in oil spill detection, where precise boundary delineation is crucial for assessing the spill's extent. Due to its ability to work well with limited data and deliver high-resolution outputs, UNET is widely used for pixel-wise classification of satellite images to identify oil-contaminated areas in oceans.

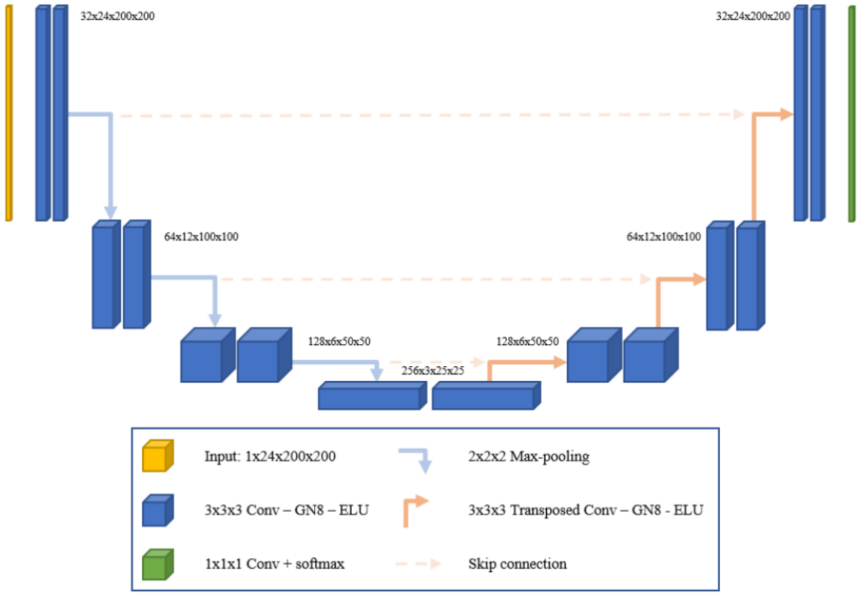


Figure 1.1 Unet Algorithm Architecture

DeepLabV3+ Algorithm

DeepLabV3+ is an enhanced version of the DeepLab family, designed for semantic segmentation with a focus on handling objects at multiple scales and complex boundaries. The architecture introduces two key innovations: Atrous Convolution and Atrous Spatial Pyramid Pooling (ASPP). Atrous convolutions, also known as dilated convolutions, allow the network to increase its receptive field without increasing the number of parameters or reducing feature map resolution. This enables the model to extract more contextual information from the image.

ASPP further strengthens this capability by applying multiple parallel atrous convolutions with different dilation rates. This setup allows the model to gather multi-scale information, which is vital in detecting oil spills that vary in shape, size, and texture. DeepLabV3+ also includes a decoder module that refines the segmentation results, especially near object boundaries, by recovering spatial details lost in the earlier layers.

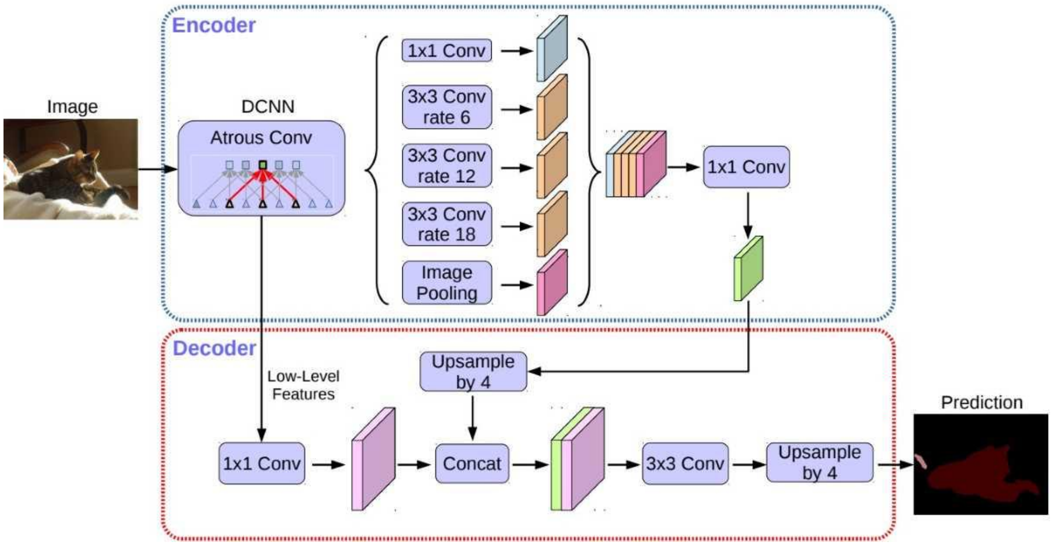


Figure 1.2 DeepLabV3+ Algorithm Architecture

For oil spill detection, DeepLabV3+ is advantageous because it minimizes false positives that typically arise due to look-alike patterns such as cloud shadows, algae blooms, or wave reflections. Its high-level feature extraction capabilities make it robust against noise and varying imaging conditions, which are common challenges in remote sensing imagery.

Hybrid Model: UNET + DeepLabV3+

To leverage the strengths of both UNET and DeepLabV3+, a hybrid architecture is implemented in this project. The core idea behind this integration is to combine UNET's spatial accuracy with DeepLabV3+'s contextual depth. UNET is proficient in capturing fine-grained edges and preserving spatial integrity, while DeepLabV3+ excels at understanding the broader context and reducing classification errors.

The hybrid model can be designed in multiple ways. One approach is to run both models independently on the same input image and merge their outputs using techniques like pixel-wise averaging, majority voting, or confidence-based fusion. Alternatively, features from one model can be fed into another, creating a unified pipeline that benefits from layered learning.

This combined approach is particularly useful for oil spill segmentation, where high precision and contextual awareness are equally important. By integrating the segmentation masks or learned features, the system becomes more resilient to anomalies and significantly improves the detection of oil spill patterns under challenging conditions such as cloud interference or low-resolution satellite images.

1.3 EXISTING SYSTEMS

- Current oil spill detection relies heavily on conventional methods like ship reports, coastal observations, and aerial patrols. These are reactive and often identify spills only after environmental harm has occurred.

- Satellite-based detection using Synthetic Aperture Radar (SAR) exists but is largely manual or semi-automated, requiring expert interpretation and offering limited real-time capabilities.

- While AIS data is available for vessel tracking, it is rarely integrated with satellite imagery. Existing systems lack automation and real-time analysis, leading to slow response times and a high rate of false positives.

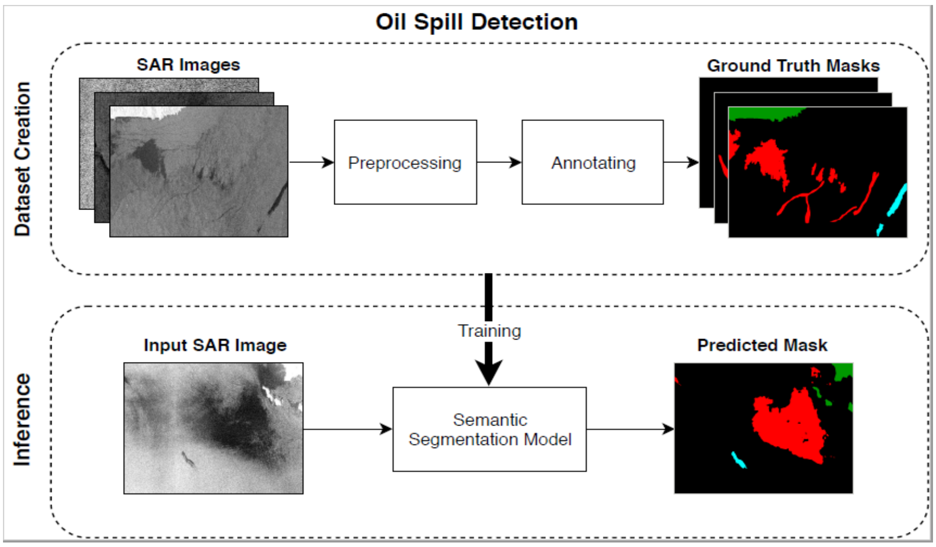


Figure 1.3.Existing System's Architecture

1.4 PROBLEMS OF EXISTING SYSTEMS

Manual Monitoring

Traditional oil spill detection methods rely on human visual interpretation of satellite images or reports from ships and coastal stations. This manual approach is slow, subjective, and not scalable for large ocean regions. Monitoring vast areas with limited personnel often results in missed incidents, especially in remote locations.

Delayed Response Time

Most conventional systems operate on a post-event analysis model, where detection happens hours or even days after the spill. This delay allows the oil to spread over larger areas, making cleanup more difficult and increasing environmental and economic impact. Real-time detection is rarely achieved in the existing setups.

Lack of Data Integration

AIS (Automatic Identification System) and satellite data are often used separately, which prevents cross-verification of vessel behavior with visual oil spill evidence. This lack of integration limits the ability to correlate unusual ship movements with potential pollution events, reducing detection accuracy.

Limited Use of Artificial Intelligence

Many current systems lack automation and intelligence, leading to poor detection rates. Without machine learning or deep learning models, these systems struggle to differentiate oil spills from similar-looking features such as cloud shadows, algae blooms, or ship wakes, leading to false positives or missed detections.

High Operational and Monitoring Costs

Using aircraft, ships, or frequent satellite tasking for continuous surveillance is expensive and resource-intensive. Maintaining a 24/7 human-monitored system is not feasible financially for many organizations or countries, especially in developing regions.

Ineffectiveness in Remote or Deep-Sea Areas

Manual or infrequent monitoring techniques fail to cover remote or high-sea areas where there are no coastal monitoring stations. These areas often experience undetected spills, which eventually reach coastlines after causing considerable harm to marine life.

Difficulty in Identifying Responsible Parties

Without AIS integration, identifying which vessel is responsible for a spill becomes a challenging task. This hinders legal and regulatory action, allowing polluters to escape accountability and encouraging repeated violations.

1.5 PROPOSED SYSTEM

The proposed system is an intelligent, automated framework that integrates AIS data, satellite imagery, and machine learning to detect oil spills in real time with high accuracy. This solution addresses the limitations of traditional methods by leveraging advanced technologies and cloud-based processing for faster and more reliable results.

AIS-Based Anomaly Detection

The system first monitors real-time Automatic Identification System (AIS) data to track vessel movements, speed, and location. Anomalies such as sudden stops, erratic paths, or prolonged idling in unauthorized areas are flagged as potential indicators of an oil spill.

Satellite Image Acquisition using Google Earth Engine (GEE)

Once an anomaly is detected, the system fetches corresponding high-resolution satellite images from platforms like Sentinel-1 or Sentinel-2 using Google Earth Engine. SAR (Synthetic Aperture Radar) is especially useful because it captures clear imagery regardless of weather or lighting conditions.

Hybrid Deep Learning Model for Oil Spill Detection

A custom-trained hybrid deep learning model (e.g., combining CNN and segmentation techniques like DeepLabV3+ or Unet) processes the satellite imagery. It distinguishes oil slick patterns from other similar visual features like algae, shadows, or waves with high accuracy.

Data Integration and Geospatial Mapping

The AIS anomalies and image-based detections are combined using geospatial techniques. This integration helps correlate vessel activity with detected spills, allowing identification of the likely source and enabling accountability.

Real-Time Alerts and Reporting

Once an oil spill is confirmed, the system sends immediate alerts and generates visual reports with vessel identity, location coordinates, time, and satellite imagery. These reports can be accessed through a web dashboard by environmental agencies for quick intervention.

1.6 BENEFITS OF PROPOSED SYSTEM

Real-Time Monitoring and Alerts

The proposed system continuously monitors vessel activities using AIS data and satellite imagery. It automatically triggers alerts when abnormal ship behavior or suspected oil spills are detected. This rapid detection helps in taking immediate action, such as dispatching cleanup teams or initiating legal procedures, thereby minimizing the spread and impact of the spill.

High Detection Accuracy with AI Integration

By leveraging a hybrid deep learning model, the system achieves higher accuracy in detecting oil spill patterns. Convolutional Neural Networks (CNNs) are trained to distinguish between true oil slicks and look-alike features such as algal blooms, cloud shadows, or natural ocean phenomena. This minimizes false positives and improves overall reliability.

Weather and Light Independence

The use of Synthetic Aperture Radar (SAR) data from satellites like Sentinel-1 ensures that the system can operate regardless of weather conditions or time of day. Unlike optical sensors, SAR can penetrate clouds and darkness, which is critical for 24/7 monitoring.

Scalable and Cloud-Based Infrastructure

Deploying the system on cloud platforms (e.g., Google Earth Engine) enables it to scale effortlessly across wide oceanic regions. It can process large volumes of data from multiple vessels and satellite passes simultaneously without requiring expensive hardware on-site.

Automated and Cost-Efficient Operations

The automation of both vessel tracking and satellite image analysis significantly reduces the need for human intervention. This not only lowers the cost of continuous surveillance but also eliminates delays associated with manual interpretation and report generation.

Geospatial Correlation for Spill Source Identification

The system can cross-reference vessel positions and behaviors with satellite-detected oil spills to pinpoint the likely source. This helps authorities assign accountability, detect illegal dumping, and take punitive actions against responsible vessels or companies.

Support for Environmental Protection Agencies

Agencies responsible for marine conservation can access detailed visual and analytical reports generated by the system. These reports can include timestamped vessel paths, annotated spill locations, and predictive Modelling of spill spread—all of which are vital for planning responses and preventing further damage.

Historical Data Analysis and Learning

By storing and analyzing past AIS movements and oil spill records, the system can learn long-term trends and identify high-risk zones. This proactive capability supports better policy-making, improves model training over time, and increases the overall efficiency of marine surveillance.

CHAPTER-2: ANALYSIS

2.1 LITERATURE REVIEW

S.No	Year	Author(s)	Article Title	Key Findings
1	2010	Chassignet, E. P., et al.	Oil spill monitoring using satellite SAR imagery and AIS data	Demonstrated the synergy of satellite SAR and AIS data for real-time oil spill monitoring and vessel identification.
2	2019	Zhang, L., et al.	Deep learning-based detection of oil spills using satellite imagery	Proposed a CNN-based method for accurate oil spill segmentation using satellite images.
3	2015	Long, J., et al.	Fully Convolutional Networks for Semantic Segmentation	Introduced FCNs, laying the groundwork for modern segmentation models like UNET and DeepLab.
4	2015	Ronneberger, O., et al.	U-Net: Convolutional Networks for Biomedical Image Segmentation	Presented the UNET architecture, highly effective for pixel-wise segmentation tasks.
5	2017	Chen, L., et al.	DeepLabv3+: Encoder-Decoder with Atrous Separable Convolution	Improved semantic segmentation using atrous convolutions, enhancing spatial accuracy.
6	2018	Scolobig, A., et al.	Predictive models for oil spill response and recovery: A comprehensive review	Reviewed modeling frameworks for oil spill response, underlining the role of predictive analytics.
7	2016	Pattiaratchi, C., et al.	Modelling the transport and fate of oil spills using hydrodynamic models	Focused on ocean current modeling to predict spill dispersion and fate.

8	2019	Huang, C., et al.	Satellite-based remote sensing for oil spill detection and monitoring: A review	Surveyed remote sensing methods, stressing the importance of image preprocessing and filtering.
9	2005	Jensen, J. R.	Remote Sensing of the Environment: An Earth Resource Perspective	Provided foundational knowledge on remote sensing techniques applicable to oil spill analysis.
10	2019	Mei, F., et al.	Application of machine learning techniques in oil spill detection and response: A review	Reviewed ML models for spill detection, including SVMs, random forests, and deep learning methods.
11	2017	Feng, L., et al.	Oil Spill Detection from Remote Sensing Imagery Using Convolutional Neural Networks	Proposed an end-to-end CNN model achieving high detection accuracy on SAR images.
12	2019	Xie, Z., et al.	Oil spill detection using satellite synthetic aperture radar and machine learning	Highlighted ML methods to reduce false positives in SAR image classification.
13	2018	Gao, J., et al.	Detection of oil spills from SAR images using deep learning	Emphasized transfer learning and data augmentation to enhance deep learning performance.
14	2020	Sun, J., et al.	Integrating satellite imagery and AIS data for oil spill detection: A review	Explored multi-source data fusion for improved spill source detection and verification.
15	2020	Zhou, C., et al.	Oil spill detection in ocean using machine learning models and SAR imagery	Proposed hybrid models to differentiate oil spills from look-alike phenomena.

16	2021	Olsson, H., et al.	A review of machine learning for marine oil spill detection and prediction	Discussed latest ML trends, including deep reinforcement learning and ensemble approaches.
17	2018	Bhatt, A., et al.	Real-time Monitoring of Ocean Spills Using Deep Learning and Satellite Images	Presented a deep learning pipeline for real-time oil spill detection and notification.
18	2020	Lee, D. J., et al.	Integration of Deep Learning and AIS for Maritime Surveillance	Showed how combining deep learning with AIS improves vessel-spill correlation and illegal dumping detection.
19	2017	Wang, Y., et al.	Deep Learning for Remote Sensing Image Classification: A Review	Provided insights into DL architectures best suited for environmental image analysis.
20	2019	Kumar, N., et al.	Deep Feature Extraction for Oil Spill Image Recognition	Emphasized hybrid CNN architectures for better classification and segmentation accuracy.

Table 2.1: Literature Survey

2.1.1 REVIEW FINDINGS

What we find from the literature review is that there is no end-to-end solution currently available that fully meets the practical requirements of accurate, real-time oil spill detection with integrated vessel tracking and minimal manual intervention. Most of the existing models and systems show limited performance, either due to technical constraints, lack of integration between satellite imagery and AIS data, or due to high operational costs. Many solutions are still at the research or prototype stage and lack scalability or usability for widespread deployment. Some rely heavily on manual interpretation, while others need high-end hardware setups or expert involvement, making them unsuitable for routine environmental monitoring by authorities. Additionally, most systems fail to provide automated alert mechanisms and lack real-time capabilities, which are crucial during oil spill emergencies. While ongoing developments by major institutions and corporations are promising, there is still a significant gap between research outcomes and practical implementation. The proposed solutions in the literature can largely be grouped into software-based image segmentation models and hardware-based monitoring systems, but none have yet achieved holistic functionality or user accessibility.

2.2 REQUIREMENT ANALYSIS

Requirement analysis is a critical phase in the software development lifecycle, wherein the needs and expectations of the stakeholders are carefully identified, analysed, validated, and documented. The objective of this phase is to determine the essential functionalities and operational attributes of the system to be developed. Given that stakeholder perspectives may often vary or even conflict, requirement analysis plays a vital role in harmonizing those expectations and translating them into precise technical and functional deliverables.

In the context of the proposed AI-based Oil Spill Detection System, requirement analysis is pivotal in understanding both the technical needs of the solution and the broader environmental, operational, and user-centric objectives. The process involves a detailed examination of the problem domain—environmental hazards due to oil spills—and the identification of system behaviours and constraints necessary to address those challenges effectively.

This phase begins with requirement elicitation, during which inputs are gathered from domain experts, environmental agencies, technical standards, and existing literature. These inputs are then subjected to rigorous analysis to determine their feasibility, relevance, and alignment with the project's scope. Once validated, the requirements are organized systematically to guide the design and development process.

These requirements can be further classified into:

1.Functional Requirements

2.Non-Functional Requirements

2.2.1 FUNCTIONAL REQUIREMENTS ANALYSIS

Functional requirements specify the core functionalities that the system must support in order to fulfill its intended purpose. In the case of the AI-based oil spill detection system, these requirements are derived from both technical specifications and the operational demands of environmental monitoring agencies, maritime authorities, and emergency response teams. These requirements define what the system should do, the conditions under which it must operate, and how it should respond to user inputs or external data sources.

The primary objective of this system is to automate the detection and monitoring of oil spills using a combination of satellite imagery, deep learning-based semantic segmentation techniques, and vessel tracking data. The following functional components are considered essential to the successful operation of the system:

Satellite Image Processing: The system must be capable of receiving and processing satellite images from reliable sources. This involves handling high-resolution imagery, converting it into usable formats, and preparing it for analysis using preprocessing techniques such as normalization, resizing, and noise reduction.

Semantic Segmentation Using AI Models: The core of the system's functionality lies in the application of advanced deep learning algorithms, such as UNET and DeepLabV3+, for semantic segmentation. These models should identify oil-affected regions in the input images with high accuracy, even in complex oceanic environments where shadows, clouds, or look-alike features may interfere with detection.

Integration of AIS Data: The system should incorporate Automatic Identification System (AIS) data to track maritime traffic in areas where spills are detected. This integration helps in associating potential spill incidents with specific vessels, thereby aiding in accountability and investigation.

Real-Time Detection and Analysis: The system must be capable of performing oil spill detection in real-time or near-real-time. This requires the deployment of efficient computational models that minimize processing time while maintaining high detection accuracy.

Automated Alert Generation: Once an oil spill is detected, the system must automatically generate alerts to the concerned authorities. These alerts should include geolocation data, time of detection, visual evidence from the satellite image, and vessel information, if available.

Visualization and Reporting Interface: A user-accessible web-based dashboard must be developed to visualize detected spills. This interface should allow users to view segmentation outputs, vessel tracking overlays, and time-series data. It should also support the generation of downloadable reports for documentation and further analysis.

Data Storage and Retrieval: The system must support secure storage of processed images, detection results, and AIS logs. This is important for maintaining historical records, training future models, and conducting comparative analyses.

System Logging and Monitoring: The system should maintain internal logs of all detection events, processing tasks, and system performance metrics to aid in auditing and performance evaluation

2.2.2 NON-FUNCTIONAL REQUIREMENTS

Non-functional requirements define the quality attributes, system constraints, and performance parameters that the system must adhere to. These requirements do not focus on the specific behaviors or outputs of the system, but rather describe how the system should behave under various conditions. For an AI-based oil spill detection system, ensuring robust non-functional requirements is crucial to achieve high reliability, usability, and operational efficiency in real-world deployment scenarios.

Some of the major non-functional requirements of the proposed system are elaborated below:

Performance and Efficiency: The system must perform oil spill detection with minimal latency, especially in real-time use cases. The deep learning models should be optimized for computational efficiency without compromising detection accuracy. Timely processing of large-scale satellite imagery and AIS data is essential for ensuring prompt decision-making during emergency scenarios.

Accuracy and Precision: The segmentation algorithms, including UNET and DeepLabV3+, must maintain a high level of detection accuracy, minimizing false positives and false negatives. The integration of AIS data should also exhibit accurate correlation with vessel movements to identify potential culprits behind oil spill incidents.

Scalability: The system should be scalable to accommodate increasing volumes of satellite data and growing areas of geographical coverage. It must support modular integration with additional data sources, such as weather data or bathymetric maps, without requiring major architectural overhauls.

Reliability and Availability: The detection platform must be highly reliable, with minimum system downtime. The availability of the application during critical times, such as environmental emergencies, must be ensured through proper server management, error handling, and fallback mechanisms.

Security and Data Privacy: All incoming and outgoing data must be protected through encryption protocols. The system should safeguard sensitive information, such as satellite data access and AIS traffic data, from unauthorized access or misuse. Role-based authentication and secure login mechanisms are mandatory for access to administrative functions.

Maintainability and Upgradability: The system should be designed in a modular and maintainable architecture, allowing future updates and enhancements with minimal disruption. This includes the ability to retrain and update deep learning models with new datasets and improved techniques.

User Experience (UX) and Usability: The graphical interface should be intuitive and user-friendly, especially for non-technical users from government bodies or environmental organizations. The web dashboard must support easy navigation, detailed visualization, and seamless interaction with segmented results and vessel tracking overlays.

Interoperability: The platform should be compatible with existing systems used by maritime agencies, including data feeds from remote sensing satellites and AIS service providers. It should support standard data formats (GeoTIFF, CSV, JSON) to enable integration and data exchange.

Portability: The software solution must be deployable on various environments, such as local servers, cloud platforms, or edge devices, depending on user requirements. It should support both on-premise and cloud-based installations to accommodate different operational contexts.

Compliance: The system must comply with relevant environmental data standards, remote sensing protocols, and governmental regulations regarding marine pollution surveillance and reporting

2.2.3 USER REQUIREMENTS

Secure User Authentication and Role-Based Access:

Only authorized users (e.g., environmental officers) can sign in and access sensitive functionalities like uploading satellite data or viewing reports.

AI-Based Satellite Image Analysis :

The system must use deep learning models (like U-Net or DeepLabV3+) to process satellite images and accurately detect oil spill regions.

Real-Time Detection and Automated Alerts:

Once an oil spill is detected, the system must display visual results with location and confidence score, and send instant alerts to authorities.

AIS Vessel Tracking Integration:

Integrate AIS data to correlate ship movements with detected oil spills, helping to identify potential responsible vessels.

Interactive Dashboard and Report Generation:

Users should have a dashboard to review detection history, view visualizations (map overlays, vessel paths), and download structured reports.

2.3 MODULE DESCRIPTION

The proposed AI-based oil spill detection system is structured into several integrated modules that work cohesively to achieve accurate and efficient segmentation of satellite images. The system leverages advanced deep learning models, image preprocessing techniques, and ensemble strategies to detect oil spills with high precision. This section outlines the technical architecture and functionality of each module.

2.3.1 Software and Technology Stack

This module outlines the programming environment, libraries, and tools utilized in the development and implementation of the oil spill detection system. The project is primarily implemented in Python, a high-level programming language widely used in artificial intelligence and machine learning applications due to its simplicity and vast ecosystem of libraries.

Programming Language:

Python 3.10 – Chosen for its robust support in deep learning frameworks and its readability for rapid prototyping.

Libraries and Frameworks:

TensorFlow 2.x / Keras: Used for building and training deep learning models such as Unet, DeepLabV3+, and the Hybrid Model.

NumPy: Utilized for numerical operations and array manipulations.

OpenCV (cv2): Used for image reading, resizing, and manipulation.

Matplotlib: Employed for visualizing images, masks, and results.

Pandas: Used for managing data-related tasks and logging.

Scikit-learn: Used for splitting datasets, computing evaluation metrics, and utility functions.

Glob / os: For file handling and dynamic directory access.

Albumentations (optional): For data augmentation during training (if applied).

Flask (optional): Considered for building a lightweight deployment interface.

All modules were developed using Jupyter Notebook and VS Code as the primary development environments. The models were trained using GPU acceleration for faster convergence.

2.3.2 Deep Learning Model Modules

This module constitutes the heart of the system, responsible for performing pixel-wise semantic segmentation using deep learning models. Three segmentation models are used: Unet, DeepLabV3+, and a custom Hybrid Model, each of which contributes uniquely to improving detection accuracy.

U-NET Model

Unet follows an encoder-decoder structure with skip connections. The encoder path extracts hierarchical features through convolution and max-pooling layers, while the decoder path reconstructs the segmentation map using upsampling and concatenation with encoder features. The output layer applies a softmax activation to yield class-wise pixel predictions.

DeepLabV3+ Model

DeepLabV3+ utilizes atrous (dilated) convolutions to extract multi-scale context and preserve resolution. It includes an Atrous Spatial Pyramid Pooling (ASPP) module and a decoder that sharpens object boundaries. This model is particularly effective in segmenting oil spills in complex backgrounds with fine boundaries.

Hybrid Model

The Hybrid Model combines components of Unet and DeepLabV3+ along with additional convolutional blocks. It is designed to capture both spatial and contextual information effectively. This approach boosts robustness and enhances segmentation accuracy under various lighting and regional variations in satellite images.

2.3.3 Model Training and Evaluation Module

This module is responsible for training and validating the three models using the preprocessed image-mask pairs.

Data is split into training and validation sets using train_test_split from scikit-learn.

Each model is compiled with the categorical cross-entropy loss function and Adam optimizer.

Training is carried out over multiple epochs with real-time monitoring of metrics such as accuracy, IoU (Intersection over Union), and Dice coefficient.

Early stopping and checkpointing mechanisms are implemented to prevent overfitting and save the best-performing model weights.

The evaluation metrics provide insight into each model’s ability to generalize on unseen test data.

2.3.4 Ensemble and Post-Processing Module

To improve the reliability of predictions, this module integrates predictions from all three models using ensemble strategies:

Majority voting: Each pixel is classified based on the majority prediction from the three models.

Probability averaging: The softmax probabilities are averaged across models, and the class with the highest average score is selected.

Weighted voting: Higher weights are assigned to models with better validation performance.

Post-processing techniques such as morphological operations or CRF (Conditional

Random Fields) may be used to refine the edges and suppress false positives.

2.3.5 Visualization and Output Module

This module handles the generation of interpretable output for end-users:
The predicted segmentation masks are mapped back to RGB color codes.
These masks are overlaid on the original satellite images to visualize oil spill regions clearly.
Visual outputs are generated using Matplotlib and can be saved as image files for documentation and reporting purposes.
This module provides qualitative insight into model predictions and facilitates manual inspection by analysts.

2.3.6 System Deployment Module

The deployment module enables the integration of the trained model into a user-accessible interface or automated pipeline.
A lightweight Flask web application can be built to allow users to upload satellite images and receive segmented results in real-time.
Alternatively, the entire system can run as a command-line tool or be scheduled via batch scripts for automated processing in large-scale monitoring systems.
Models are stored in .h5 format and loaded dynamically for inference.
This module ensures the system is practically deployable for real-world applications such as maritime surveillance, oil spill response systems, and satellite monitoring dashboards.

2.4 FEASIBILITY STUDY

A feasibility study is an analysis that takes all a project’s relevant factors into account including economic, technical, legal, and scheduling considerations to ascertain the likelihood of completing the project successfully. A feasibility study is important and essential to evolute any proposed project is feasible or not. A feasibility study is simply an assessment of the practicality of a proposed plan or project.
The main objectives of feasibility are mentioned below:
To determine if the product is technically and financially feasible to develop, is the main aim of the feasibility study activity. A feasibility study should provide management with enough information to decide:

- Whether the project can be done.
- To determine how successful your proposed action will be.
- Whether the final product will benefit its intended users.
- To describe the nature and complexity of the project.
- What are the alternatives among which a solution will be chosen (During subsequent phases)
- To analyze if the software meets organizational requirements.

There are various types of feasibility that can be determined. They are:

Operational – Define the urgency of the problem and the acceptability of any solution, includes people-oriented and social issues: internal issues, such as manpower problems, labor objections, manager resistance, organizational conflicts, and policies; also, external issues, including social acceptability, legal aspects, and government regulations.

Technical: Is the feasibility within the limits of current technology? Does the technology exist at all? Is it available within a given resource?

Economic – Is the project possible, given resource constraints? Are the benefits that will accrue from the new system worth the costs? What are the savings that will result from the system, including tangible and intangible ones? What are the development and operational costs?

Schedule – Constraints on the project schedule and whether they could be reasonably met.

2.4.1 TECHNICAL FEASIBILITY

The proposed system is technically feasible due to the use of freely available public datasets, including Sentinel-1 and Sentinel-2 satellite imagery and AIS (Automatic Identification System) data. This ensures the system remains cost-effective and scalable without requiring proprietary data.

It utilizes well-established and widely supported frameworks such as TensorFlow, Keras, and PyTorch for building and training deep learning models. VS Code serves as a robust development environment, supporting various programming languages and extensions for smooth development and debugging.

The required hardware configurations are compatible with mid-range GPUs and cloud platforms, making it efficient to process large image datasets and conduct real-time predictions, ensuring the system runs smoothly in both local and cloud-based deployments.

2.4.2 OPERATIONAL FEASIBILITY

The system is designed with a user-friendly interface, ensuring that environmental officers, maritime authorities, and analysts can easily operate and interpret the results without needing deep technical expertise.

Through visualization tools such as overlay maps and zoomable satellite imagery, users can intuitively navigate and analyze oil spill regions, vessel paths, and detection outcomes.

Its modular architecture ensures each component (AIS analysis, image processing, model prediction, visualization) operates independently, enabling easy maintenance, upgrades, and troubleshooting without affecting the whole system.

2.4.3 BEHAVIORAL FEASIBILITY

The system supports easy user adaptation by providing clear training materials, walkthroughs, and sample datasets that allow users to quickly understand and operate.

It presents interpretable visual insights, such as detection confidence scores, vessel locations, and time stamps, that help users make decisions and take timely action, promoting trust and engagement.

2.5 PROCESS MODEL USED

To ensure a systematic and efficient development of our AI-powered oil spill detection and vessel tracking system, we adopted the Incremental Process Model. This model was selected because of its iterative and modular structure, allowing each component—such as satellite image processing, AIS data analysis, and visualization tools—to be developed, tested, and integrated in phases.

With each increment, the system was enhanced based on user feedback and performance evaluations, enabling early detection of issues, continuous improvement of deep learning models, and effective integration of geospatial analysis. This approach also facilitated parallel development and testing, ensuring faster deployment while maintaining high accuracy and reliability in real-time detection and reporting.

2.6 HARDWARE AND SOFTWARE REQUIREMENTS

HARDWARE

- Processor – Intel Core i5
- Hard Disk – 512GB SSD
- RAM – 16GB
- GPU – NVIDIA RTX series (optional, for accelerated training)
- Operating System – Windows 10 or higher

SOFTWARE

Python based Computer Vision and Deep Learning libraries will be exploited for the development and experimentation of the project.

- Programming Language – PYTHON 3.10 or Below
- IDE – Visual Studio Code
- TensorFlow, OpenCV, Flask, React js

2.7 SRS SPECIFICATION

2.7.1 INTRODUCTION

2.7.1.1 Purpose

This document provides a detailed description of the functional, non-functional, and system requirements for the AI-based Oil Spill Detection and Vessel Tracking System.

The system will enable authorized users to upload satellite images for analysis, detect oil spills using deep learning models (like U-Net and DeepLabV3+), integrate AIS data for vessel identification, and provide real-time alerts and interactive visualizations for effective maritime environmental monitoring.

2.7.1.2 Scope

The system facilitates automated detection of marine oil spills using AI models integrated with Synthetic Aperture Radar (SAR) satellite images and AIS vessel tracking data. Key features include:

- Deep learning-based spill detection.
- AIS data integration for vessel correlation.

- Real-time visualizations and reports.

2.7.1.3 Definitions, Acronyms, and Abbreviations

- **SAR:** Synthetic Aperture Radar
- **AIS:** Automatic Identification System
- **CNN:** Convolutional Neural Network

2.7.2 OVERALL DESCRIPTION

2.7.2.1 ProductPerspective

The system will act as a comprehensive platform integrating satellite remote sensing, deep learning models, and maritime data analytics. It is designed to enhance existing manual spill monitoring systems with AI-powered automation and geospatial insights.

2.7.2.2 Product Features

Secure login and role-based access.
Upload and process Sentinel-1/Sentinel-2 satellite images.
Hybrid AI model-based spill detection (U-Net, DeepLabV3+).
AIS data integration to track suspicious vessels.

2.7.2.3 User Classes and Characteristics

Environmental Officers: Upload images, view detections, analyze reports.
Admin Analysts: Manage users, verify detections, oversee system operations.
Developers: Maintain and update the system backend and ML models.

2.7.3. FUNCTIONAL REQUIREMENTS

2.7.3.1 Authentication and Access:

Allow secure registration/login/logout.
Role-based access for officers, admins, and analysts.

2.7.3.2 Image Upload and Processing:

Upload SAR images or use linked sources.
Detect oil spills using AI models and mark regions.

2.7.3.3 AIS Vessel Analysis:

Overlay AIS data with satellite images.

Identify vessel anomalies near spills.

2.7.3.4 Alert System and Reports:

Auto-trigger alerts with location and time.

Downloadable spill reports with image overlays.

2.7.3.5 Historical Data and Dashboards:

Store past detections for each user.

Display detection history and maps on user dashboards.

2.7.4. NON-FUNCTIONAL REQUIREMENTS

2.7.4.1 Performance

Detection results within 30 seconds post-upload.

2.7.4.2 Reliability

99.9% uptime and robust image handling.

2.7.4.3 Usability

Interactive interface with zoom and map overlays.

2.7.4.4 Scalability

Encrypted data transmission and secure access.

2.7.4.5 Security

Handle large image files and real-time vessel data.

2.7.5. SYSTEM REQUIREMENTS

2.7.5.1 Hardware Requirements

- **Processor:** Intel Core i5 or better.
- **RAM:** 8GB minimum.
- **Storage:** At least 256GB SSD.

2.7.5.2 Software Requirements

- **Operating System:** Windows 10 or higher.
- **Frameworks/Tools:** Python, TensorFlow, or PyTorch for CNN model.

CHAPTER-3: DESIGN PHASE

3.1 DESIGN CONCEPTS

Design concepts in software engineering provide a foundation for developing scalable, maintainable, and efficient systems. These concepts help in structuring the system in a way that ensures smooth functionality, ease of maintenance, and enhanced user experience.

1. Modularity

The system is divided into independent modules that handle different functionalities:

Satellite Image Processing Module: Detects oil spills using segmentation models (U-Net, DeepLabV3+).

AIS Data Analysis Module: Monitors vessel movements and detects behavioral anomalies.

Integration Module: Correlates spill locations with vessel paths.

Visualization & Reporting Module: Displays results on maps and generates alerts.

2. Abstraction

Only essential functionalities are exposed to users while hiding internal complexities:

The deep learning models abstract the segmentation process and return results with confidence scores.

Users interact with a simple interface to upload images or view vessel movements.

3. Encapsulation

Data and logic are protected to prevent unauthorized access or manipulation:

AIS data processing and oil spill classification logic are securely implemented in backend services.

Secure APIs control how frontend modules access backend functions.

4. Separation of Concerns (SoC)

Each component of the system is assigned a dedicated responsibility:

Frontend (JS): Handles UI and user interactions.

Backend (Flask/Python): Performs image processing, AI predictions, and AIS data correlation.

Database (Firebase): Stores spill data, vessel records, and system logs.

5. **Reusability**

Detection models (U-Net, DeepLabV3+) can be retrained with new datasets without changing the interface.
AIS anomaly detection logic can be reused across different marine zones or vessel categories.

6. **Scalability**

The system is designed to handle large datasets and multiple concurrent users:

Cloud-based storage and processing support scalability.

Modular microservices allow independent scaling of each component (e.g., image processing service).

7. **User-Centric Design**

The interface is designed for simplicity and clarity:

Interactive maps for easy navigation and understanding of detected spills.

Clear visualization of vessel paths and spill zones for quick decision-making.

AGILE METHODOLOGY

Phases of the Agile Development Cycle

Figure 3.1 Agile Methodology

1. **Requirement Gathering and Sprint Planning**

   We began by identifying core functionalities such as satellite image processing, oil spill detection using AI models, AIS-based vessel tracking, visualization, and alert generation. The development was broken into time-bound sprints, each with specific goals. Tools and technologies were selected, including TensorFlow and OpenCV for image processing, Google Earth Engine for satellite data, Flask for backend logic, ReactJS for frontend development, and Firebase for database and hosting.

2. **Sprint-wise Development and Integration**

   Each sprint focused on building and testing a specific module:

   - Sprint 1: Satellite Image Processing and Spill Detection Processed SAR images from Sentinel-1 and implemented segmentation using deep learning models like UNet and DeepLabV3+. Accuracy and prediction quality were evaluated and improved based on model tuning.
   - Sprint 2: AIS Data Analysis and Vessel Correlation Integrated AIS data to detect vessel anomalies such as sudden stops or abnormal movement. These anomalies were correlated with spill zones identified in satellite images.
   - Sprint 3: Real-Time Visualization and User Interface Developed an interactive dashboard using ReactJS. Users could view spill zones, vessel tracks, and receive alerts in a geospatial format for better decision-making.
   - Sprint 4: Alert System and Report Generation Implemented automated alert generation for confirmed spills. Reports included vessel information, confidence scores, and were available for download and review by environmental agencies.

3. **Testing and Feedback**

   After each sprint, unit and integration testing were conducted. Users provided feedback on system usability, accuracy of detection, and interface clarity. Improvements were implemented in the following sprint cycles to enhance overall system performance.

4. **Deployment and Maintenance**

   The application was deployed using cloud-based services like Firebase for hosting and storage. The system was monitored for performance, and updates were made regularly to improve model accuracy and expand AIS data support.

Advantages of Using the Agile Model

- Flexibility: The model allowed changes at any stage based on user needs or technical challenges.

- Early issue identification: Frequent testing helped catch problems early in the cycle.
- Continuous improvement: Regular iterations enabled us to enhance system performance progressively.
- User-focused development: Real-time feedback ensured the system remained aligned with the expectations of its target users.

By using the Agile Process Model, we developed a scalable and responsive oil spill detection system that combines satellite imagery, AIS data, and AI models to deliver real-time environmental monitoring and vessel tracking.

3.2 DESIGN CONSTRAINTS

Design constraints define the limitations and restrictions that influence the development of a system. These constraints ensure that the system remains feasible, efficient, and aligned with technical and business requirements. In this project, several design constraints impact the architecture, performance, security, and usability.

1. Functional Constraints

Data Type & Processing Limitations :

The system must process AIS data and satellite images efficiently

Maximum image resolution constraints to optimize storage and computation

Large datasets must be handled with distributed processing

Detection Accuracy :

AI-based detection must minimize false positives and negatives

Hash-based comparison for efficient data indexing

Cross-validation with multiple satellite sources

2. Performance Constraints

Storage & Compute Efficiency :

Cloud storage limits (AWS S3, Google Cloud Storage)

Optimized model inference for real-time processing

Efficient memory management for large-scale analysis

Latency Considerations :

Image processing must be completed within an acceptable delay (<2 sec)

Database queries for vessel tracking should not exceed 200ms

Network interactions must be optimized for high throughput

3. Security Constraints

Authentication & Access Control :

Must use secure API authentication mechanisms (e.g., API keys, token-based authentication)

Role-based access control to prevent unauthorized data modifications

Data Privacy & Compliance :

AIS data and satellite images should be encrypted in transit (TLS 1.2/1.3) and at rest (AES-256)

Must comply with GDPR, HIPAA, or relevant maritime data protection regulations

No unauthorized sharing of stored vessel and spill detection metadata

4. Technical Constraints

Google Maps Satellite Images Constraints :

Limited resolution and real-time data availability may affect detection accuracy

API usage limits and costs could impact large-scale data processing

Weather conditions and cloud cover may obstruct clear image acquisition

Hardware & Infrastructure Constraints :

Hosted on scalable cloud-based services for real-time data processing

Must work on both desktop and mobile platforms for remote monitoring

Edge computing might be required for efficient vessel tracking and spill detection in large-scale operations

5. Usability & User Experience Constraints

Alert System Constraints :

Detection alerts must be non-intrusive

Allow users to override alerts in case of confirmed spill events

Multi-Platform Support :

Cross-platform compatibility (Windows, Mac, Linux, Android, iOS)

User-friendly dashboards for real-time monitoring

6. Business & Cost Constraints

Storage Cost Management :

Cloud storage costs must be optimized

Automatic storage tiering for cost-efficient archiving

Maintenance & Support :

Regular updates for AI models and detection algorithm

Must be easily maintainable by a small development team

3.3 CONCEPTUAL DESIGN

Conceptual design focuses on the high-level structure of the project. It provides an abstract overview of how different components interact, ensuring a clear understanding of system functionality before implementation.

1. System Overview

The Oil Spill Detection System is a cloud-based platform that integrates AIS data and satellite images to detect and monitor oil spills. It leverages AI-driven analysis to enhance accuracy and optimize real-time tracking.

Key Components

A. **User Interface :**

Dashboard: Displays detected spills, vessel activity, and alerts

Image Processing Section: Upload and analyze satellite images

Alert System: Real-time notifications via UI pop-ups and email

User Authentication: Secure login, role-based access

B. **Backend Processing :**

Image Analysis Engine: Processes satellite images for spill detection

AI Detection Model: Uses DeepLabV3+ and Unet for segmentation

Vessel Correlation Module: Matches spills with AIS data

Notification Service: Alerts relevant authorities

Logging & Analytics: Tracks detection history and system performance

C. **Database & Storage Layer :**

Metadata Database : Stores AIS and spill detection records

Cloud Storage : Maintains satellite images

D. **Security & Compliance :**

Authentication & Authorization: API key-based access

Encryption: TLS for transmission, AES-256 for data storage

Compliance: Adheres to GDPR, MARPOL, and environmental policies

Expected Outcomes

Efficient Spill Monitoring: Utilizes advanced algorithms and real-time satellite data to detect oil spills in marine environments as soon as they occur. This allows for timely response and mitigation, minimizing environmental impact. The system leverages various data sources such as satellite imagery, AIS data, and environmental sensors for accurate spill detection and location tracking.

Enhanced Maritime Surveillance: Correlates vessel activities with the detected oil spills by integrating Automatic Identification System (AIS) data, tracking vessel movements in proximity to the spill. This feature helps identify potential sources of the spill, monitor ship behavior, and analyze patterns of responsibility or negligence. It assists authorities in making informed decisions for investigation and enforcement.

Scalable Cloud Integration: The system is designed to seamlessly integrate with major cloud platforms like AWS, Google Cloud, and Azure, allowing for flexible scaling of resources. Whether handling small-scale incidents or large-scale spill events, cloud computing ensures reliable data processing, storage, and real-time analysis. It also supports high availability and disaster recovery, ensuring continuous monitoring and operations.

User-Friendly Interface: Provides a visually appealing and intuitive dashboard that allows users to monitor oil spills, vessel movements, and other related data at a glance. The interface includes real-time alerts, heatmaps, and visual indicators that provide insights into spill severity, potential risks

Conceptual Design Diagrams:

Use Case Diagram:

A use case illustrates a unit of functionality provided by the system. The main purpose of the use-case diagram is to help development teams visualize the functional requirements of a system, including the relationship of “actors” (human beings) to essential processes, as well as the relationships among different use cases.

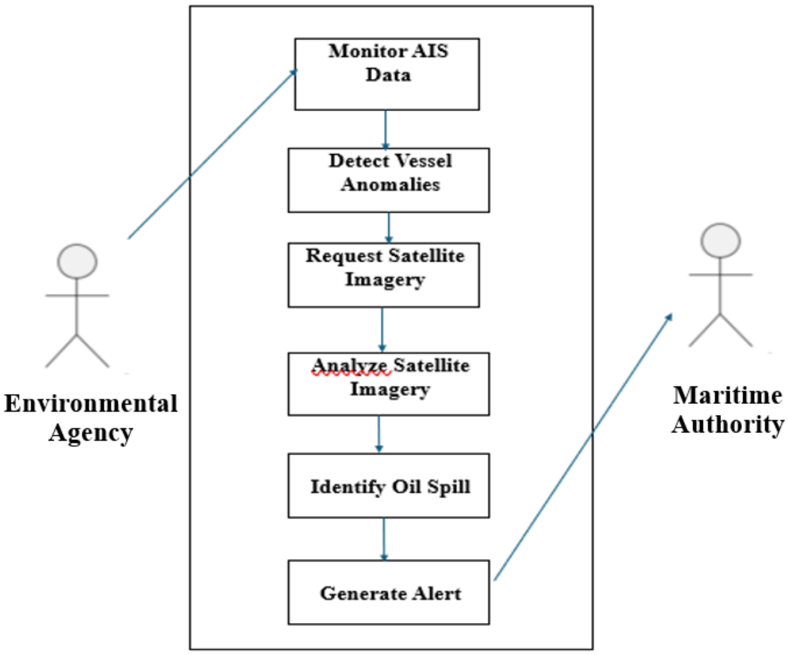


Figure 3.2 Use case diagram for end user

Class Diagram:

Class diagram in the Unified Modeling Language (UML) is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among objects.

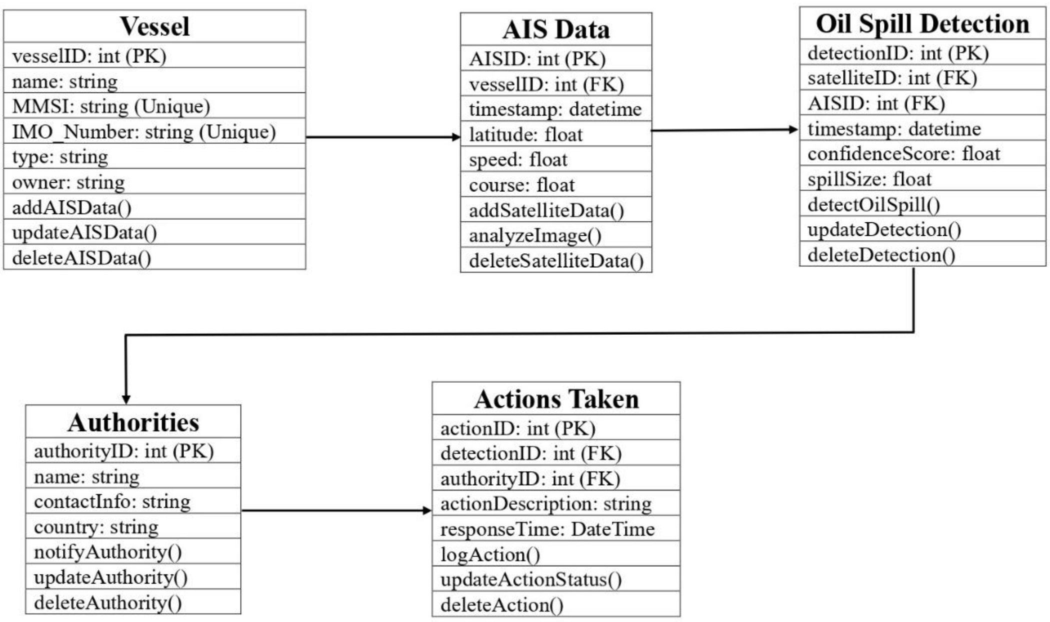


Figure 3.3 Class diagram

Sequence Diagram:

The sequence diagram outlines the interaction between the User, Web Interface, Backend System, AI Detection Models, Satellite & AIS Data Sources, and Database in the oil spill detection system.

1. **Data Initialization:**
   The backend system periodically retrieves real-time AIS data (vessel positions) and satellite imagery (Sentinel-1/Sentinel-2) through scheduled tasks or upon user request.
2. **User Interaction:**
   The user accesses the web application, where they can initiate detection by selecting a region or time frame. The request is forwarded to the backend system.
3. **Oil Spill Detection:**
   The backend processes satellite images using AI models (Hybrid DeepLabV3+/Unet) to detect potential oil spills via semantic segmentation. The models return spill zones along with confidence scores.
4. **Vessel Correlation:**
   In parallel, AIS data is analyzed to detect vessel anomalies (e.g., sudden stops or unusual course changes). The system correlates vessel positions with detected spill zones to identify potentially responsible vessels.
5. **Result Aggregation:**
   The backend compiles results — including detected spills, vessel IDs, and locations — and stores this information in the database for future reference.
6. **Visualization and Reporting:**
   The processed data is returned to the web interface, where the user can view spill zones and vessels on an interactive map, download reports, and receive alerts.
7. **Historical Access:**
   Users can also view past incidents by querying the database through the interface, retrieving historical spill detections and vessel data.

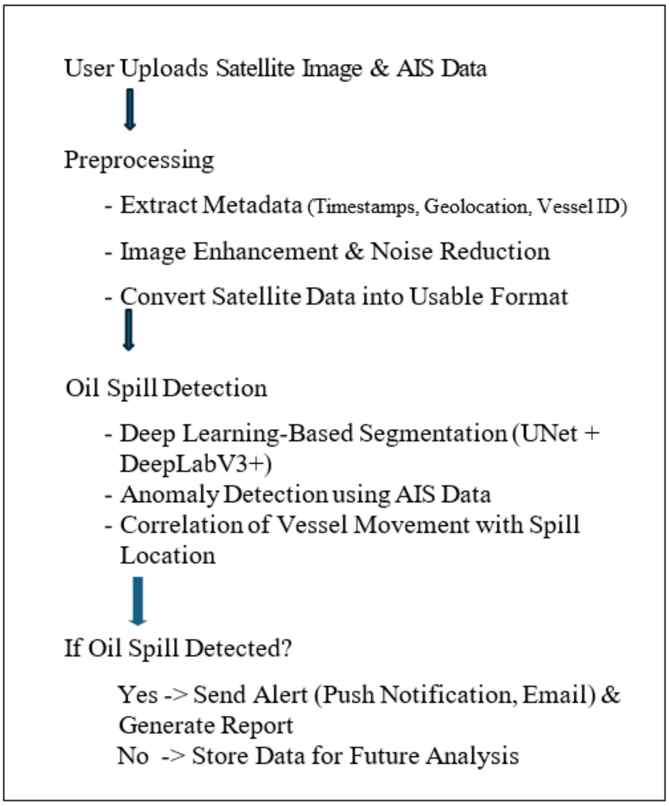


Figure 3.4 Sequence diagram

3.4 LOGICAL DESIGN

The system consists of several interconnected modules, each responsible for distinct operations. The logical design is structured into the following components:

Logical Design of the System:

The system consists of several interconnected modules, each responsible for distinct operations. The logical design is structured into the following components:

1. Input :

The system receives AIS data and satellite images as input for processing

Images are preprocessed to enhance contrast and remove noise before segmentation

2. Unet :

Unet is a deep learning-based segmentation model used to identify oil spills

It consists of an encoder-decoder architecture with skip connections for precise segmentation

Unet Encoder :

The encoder extracts meaningful features from satellite images through convolutional layers

It progressively reduces spatial dimensions while increasing feature depth for better context understanding

Unet Bottleneck :

The decoder upsamples the compressed features to restore the spatial dimensions of the image

It merges extracted features with original input data to accurately delineate oil spill regions

Unet decoder :

The decoder upsamples the compressed features to restore the spatial dimensions of the image

It merges extracted features with original input data to accurately delineate oil spill regions

3. DeepLabV3:

DeepLabV3+ Backbone:

Uses a ResNet50 or Xception architecture to extract deep features from images

Captures multi-scale context information, improving segmentation accuracy

ASPP Module:

Atrous Spatial Pyramid Pooling (ASPP) enhances feature extraction at multiple scales

Uses different dilation rates to expand the receptive field and capture global context

DeepLab Decoder:

Refines segmentation maps by merging ASPP output with low-level features

Upsamples feature maps to the original image resolution for precise segmentation

4. Hybrid Feature Extraction :

Combines feature maps from both Unet and DeepLabV3+ models

Enhances segmentation accuracy by leveraging both local and global contextual features

5. Output:

Generates refined segmentation maps highlighting oil spill region

Outputs are visualized on interactive geospatial dashboards for real-time monitoring and analysis

Logical Tools & Techniques Used

Image Processing & Feature Extraction:

OpenCV, Scikit-image for image preprocessing and enhancement

Hybrid deep learning model (Unet + DeepLabV3+) for oil spill segmentation

Perceptual hashing techniques for image similarity detection

Machine Learning Models:

Deep learning-based segmentation using Unet and DeepLabV3+

CNN-based image classification (ResNet, VGG) for vessel identification

Metadata Analysis:

Satellite image metadata extraction for environmental monitoring

AIS data correlation with detected oil spills

Notification System

Real-time alerts for detected oil spills via WebSockets

API-driven push notifications for maritime authorities

Automated email and SMS alerts for environmental agencies

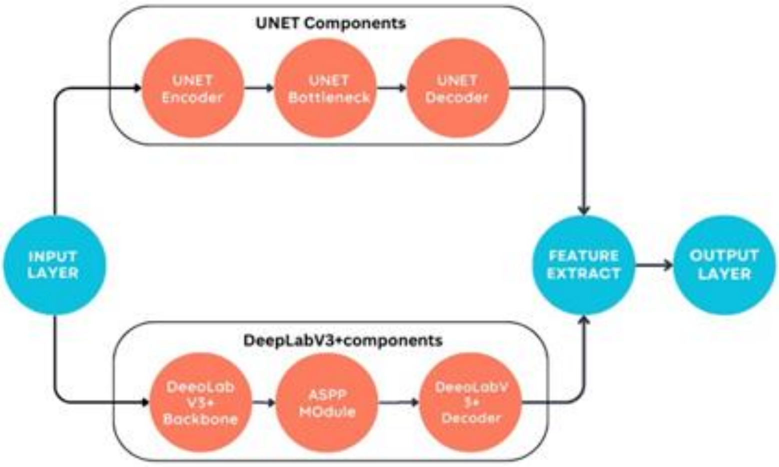


Figure 3.5 Logical Design

3.5 ARCHITECTURAL DESIGN

(1) **Data Ingestion Layer**

Accepts satellite images and AIS data as input

Extracts metadata such as vessel ID, timestamps, and geolocation

Preprocesses images through noise reduction and enhancement

(2) **Processing Layer**

- **Feature Extraction**

  Satellite Images: Segmentation using Unet and DeepLabV3+

  AIS Data: Pattern recognition for anomaly detection

  Metadata: Correlates timestamps and geolocation for spill tracking

- **Oil Spill Detection Engine:**

  Machine learning-based segmentation for oil spill identification

  Anomaly detection in AIS data to trace responsible vessels

  Correlation analysis between satellite imagery and vessel movement

(3) Decision & Alert Layer

Determines whether the detected anomaly is an oil spill

Classifies spills based on confidence scores and severity

Sends alerts through push notifications, emails, and dashboards

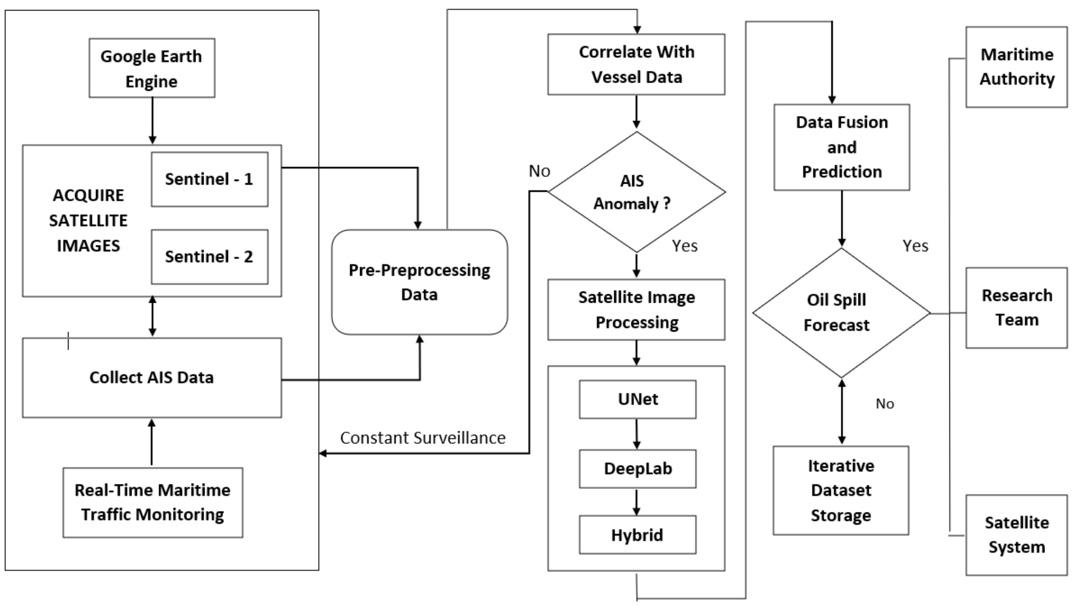


Figure 3.6 Architectural Design

3.6 ALGORITHM DESIGN

Step 1: Data Ingestion

Input: UploadRequest(satellite_image, AIS_data, timestamp)

Process:

- Extract metadata (geolocation, vessel ID, timestamps)
- Store in temporary storage for preprocessing

Step 2: Preprocessing & Feature Extraction

Input: satellite_image, AIS_data

Process:

- **Satellite Images**:
  - Apply noise reduction and contrast enhancement
  - Extract key features using Unet and DeepLabV3+
  - Compute perceptual hash for similarity detection
- **AIS Data**:
  - Extract vessel trajectories and timestamps
  - Detect anomalies using statistical and ML-based method
  - Compute geospatial correlations with detected oil spills

Step 3: Oil Spill Detection Engine

Input: processed_image, AIS_data, extracted_features

Process:

Image-Based Oil Spill Detection

Apply Unet and DeepLabV3+ models for segmentation

Extract spill boundaries and classify severity levels.

AIS Anomaly Detection

Compare vessel trajectories with known spill locations

Detect unusual patterns (e.g., sudden stops, deviations)

Correlation Analysis

Match detected spills with potential responsible vessels

Validate detection confidence using geospatial and temporal data

Step 4: Decision Making

Input: detection_scores, anomaly_flags

Process:

Threshold-based classification:

score = 1 → Confirmed Oil Spill (High Confidence)

score = 0 → False Positive (Low Confidence)

- Generate Duplicate Status report

Step 5: Alert & Notification System Input: detection_status

Process:

If Confirmed Oil Spill:

Notify environmental agencies and maritime authorities

Generate automated reports for investigation

If Potential Spill:

Issue real-time alerts for further analysis

Send Alerts:

WebSocket real-time notifications

API call for push notifications

Email summary to relevant stakeholders

3.7 DATABASE DESIGN

Users – Stores user details and access levels

Satellite_Images – Stores uploaded satellite image metadata

AIS_Data – Stores vessel movement data and timestamps

Image_Features – Stores extracted image segmentation features

AIS_Anomalies – Stores detected vessel anomalies for correlation analysis

Spill_Detections – Stores detected oil spills and confidence scores

Alerts – Stores alerts sent to authorities and environmental agencies

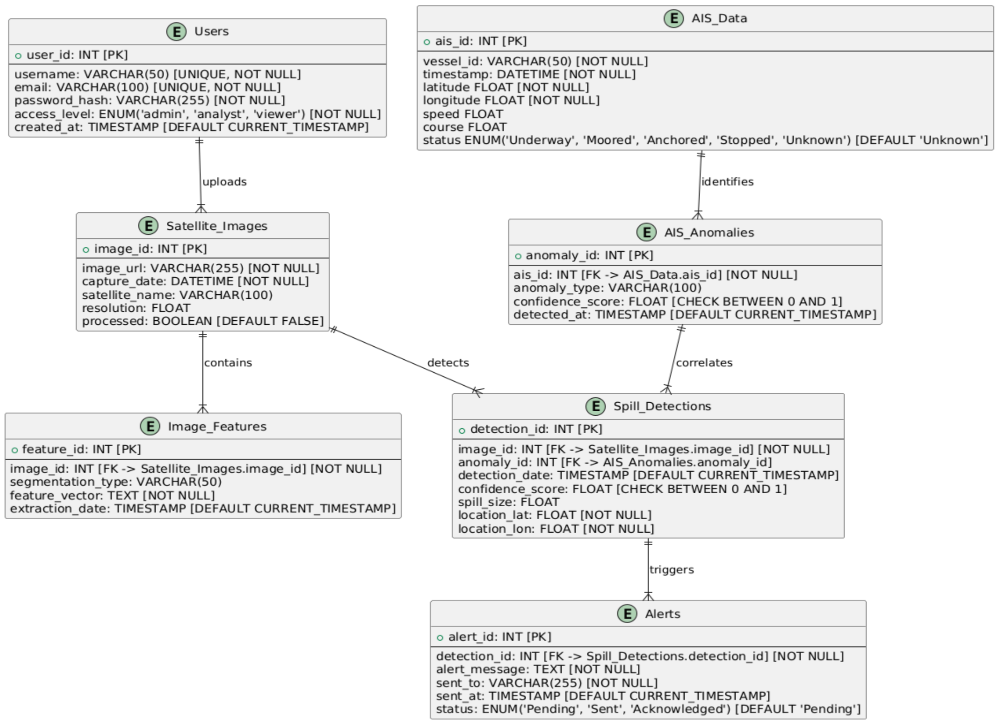


Figure 3.7 Database Design

1. AIS Data Processing Module

- **Purpose:** Processes Automatic Identification System (AIS) data to track vessel movements and detect anomalies that could indicate an oil spill
- **Components:**
    - **Data Collection:** Extracts vessel position, speed, and trajectory data
    - **Anomaly Detection:** Identifies irregular vessel behavior, such as sudden speed changes or erratic movements
    - **Correlation with Spill Events:** Links detected oil spills with nearby vessels using time and location matching

4. Satellite Image Processing Module

- **Purpose:** Uses Sentinel-1 and Sentinel-2 satellite imagery to detect oil spills
- **Components:**
    - **Image Acquisition:** Retrieves satellite images from Google Earth Engine
    - **Preprocessing:** Normalizes, resizes, and despeckles images to enhance clarity
    - **Segmentation Models:** Uses deep learning models (U-Net and DeepLabV3+) to highlight oil spill regions

4. Deep Learning-Based Detection Module

- **Purpose:** Implements machine learning models to automatically identify oil spills
- **Components:**
    - **U-Net Model:** Focuses on pixel-level accuracy for detecting oil slicks
    - **DeepLabV3+ Model:** Uses multi-scale feature extraction to improve segmentation
    - **Hybrid Model:** Combines U-Net and DeepLabV3+ to enhance detection precision

4. Data Integration & Correlation Module

- **Purpose:** Combines AIS and satellite data to improve accuracy
- **Components:**
    - **Geospatial Mapping:** Aligns detected spills with vessel positions

- **Cross-Validation:** Confirms spills using multiple sources before flagging incidents

4. **Visualization & User Interface Module**

- **Purpose:** Displays detected oil spills and vessel movements interactively
- **Components:**
  - **Geemap Integration:** Creates an interactive map with spill overlays
  - **Graphical Reports:** Provides visual insights into detected spills and affected areas

4. **System Deployment & Performance Evaluation Module**

- **Purpose:** Ensures model reliability and system efficiency
- **Components:**
  - **Performance Metrics:** Evaluates accuracy, precision, and recall of detection models
  - **Scalability Testing:** Assesses real-time processing capability
  - **Future Improvements:** Incorporates weather data and real-time alerts for better predictions

CHAPTER-4: CODING & OUTPUT SCREENS

4.1 CODING

The following code provides a sample implementation demonstrating various deep learning techniques for image segmentation, including models such as U-Net, DeepLabV3+, and other relevant architectures. It covers key components like data preprocessing, model definition, training loops, evaluation metrics, and visualization of results. This example is intended to give an overview of the workflow involved in building segmentation models. Please note that this is only a simplified version for reference. To access the complete project with all models, detailed functionalities, and extended features,

Visit the full GitHub repository at

https://github.com/uday1730/Real-Time-Oil-Spill-Detection-Using-AIS-And-Satellite-Data-Integration

UNET CODE

```
import tensorflow as tf
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Conv2D, MaxPooling2D, Dropout,
Conv2Dtranspose, concatenate
from tensorflow.keras.optimizers import Adam

# Define U-Net model
def Unet(input_shape=(256, 256, 3), num_classes=5):
    inputs = Input(input_shape)

    # Encoder
    c1 = Conv2D(16, (3, 3), activation='relu', padding='same')(inputs)
    c1 = Dropout(0.1)(c1)
    c1 = Conv2D(16, (3, 3), activation='relu', padding='same')(c1)
    p1 = MaxPooling2D((2, 2))(c1)
```

```
c2 = Conv2D(32, (3, 3), activation='relu', padding='same')(p1)
c2 = Dropout(0.1)(c2)
c2 = Conv2D(32, (3, 3), activation='relu', padding='same')(c2)
p2 = MaxPooling2D((2, 2))(c2)

c3 = Conv2D(64, (3, 3), activation='relu', padding='same')(p2)
c3 = Dropout(0.2)(c3)
c3 = Conv2D(64, (3, 3), activation='relu', padding='same')(c3)
p3 = MaxPooling2D((2, 2))(c3)

c4 = Conv2D(128, (3, 3), activation='relu', padding='same')(p3)
c4 = Dropout(0.2)(c4)
c4 = Conv2D(128, (3, 3), activation='relu', padding='same')(c4)
p4 = MaxPooling2D(pool_size=(2, 2))(c4)

# Bottleneck
c5 = Conv2D(256, (3, 3), activation='relu', padding='same')(p4)
c5 = Dropout(0.3)(c5)
c5 = Conv2D(256, (3, 3), activation='relu', padding='same')(c5)

# Decoder
u6 = Conv2Dtranspose(128, (2, 2), strides=(2, 2), padding='same')(c5)
u6 = concatenate([u6, c4])
c6 = Conv2D(128, (3, 3), activation='relu', padding='same')(u6)
c6 = Dropout(0.2)(c6)
c6 = Conv2D(128, (3, 3), activation='relu', padding='same')(c6)

u7 = Conv2Dtranspose(64, (2, 2), strides=(2, 2), padding='same')(c6)
u7 = concatenate([u7, c3])
c7 = Conv2D(64, (3, 3), activation='relu', padding='same')(u7)
c7 = Dropout(0.2)(c7)
c7 = Conv2D(64, (3, 3), activation='relu', padding='same')(c7)

u8 = Conv2Dtranspose(32, (2, 2), strides=(2, 2), padding='same')(c7)
```

```
    u8 = concatenate([u8, c2])
    c8 = Conv2D(32, (3, 3), activation='relu', padding='same')(u8)
    c8 = Dropout(0.1)(c8)
    c8 = Conv2D(32, (3, 3), activation='relu', padding='same')(c8)

    u9 = Conv2Dtranspose(16, (2, 2), strides=(2, 2), padding='same')(c8)
    u9 = concatenate([u9, c1], axis=3)
    c9 = Conv2D(16, (3, 3), activation='relu', padding='same')(u9)
    c9 = Dropout(0.1)(c9)
    c9 = Conv2D(16, (3, 3), activation='relu', padding='same')(c9)

    # Output layer with softmax activation for multi-class
    outputs = Conv2D(num_classes, (1, 1), activation='softmax')(c9)

    model = Model(inputs=[inputs], outputs=[outputs])
    return model

# Create and compile the model
model = Unet(input_shape=(256, 256, 3), num_classes=5)
model.compile(optimizer=Adam(), loss='categorical_crossentropy',
metrics=['accuracy'])

# Summary
model.summary()

# Example Training (dummy dataset below)
# Replace X_train, y_train with actual image & one-hot encoded mask data
import numpy as np
X_train = np.random.rand(10, 256, 256, 3)
y_train = np.random.rand(10, 256, 256, 5)  # one-hot mask (5 classes)

# Train the model
model.fit(X_train, y_train, batch_size=2, epochs=5, validation_split=0.1)
```

DeepLabV3+ CODE

```
import tensorflow as tf
from tensorflow.keras.layers import (
    Input, Conv2D, SeparableConv2D, BatchNormalization, Activation, Dropout,
    UpSampling2D, GlobalAveragePooling2D, Reshape, Concatenate
)
from tensorflow.keras.models import Model
from tensorflow.keras.applications import ResNet50

# Constants
input_shape = (256, 256, 3)
IMG_CLASSES = 5

# ASPP module
def ASPP(inputs):
    shape = tf.shape(inputs)

    y1 = Conv2D(256, 1, padding='same', use_bias=False)(inputs)
    y1 = BatchNormalization()(y1)
    y1 = Activation('relu')(y1)

    y2 = SeparableConv2D(256, 3, dilation_rate=6, padding='same',
use_bias=False)(inputs)
    y2 = BatchNormalization()(y2)
    y2 = Activation('relu')(y2)

    y3 = SeparableConv2D(256, 3, dilation_rate=12, padding='same',
use_bias=False)(inputs)
    y3 = BatchNormalization()(y3)
    y3 = Activation('relu')(y3)

    y4 = SeparableConv2D(256, 3, dilation_rate=18, padding='same',
use_bias=False)(inputs)
```

```
    y4 = BatchNormalization()(y4)
    y4 = Activation('relu')(y4)

    y5 = GlobalAveragePooling2D()(inputs)
    y5 = Reshape((1, 1, -1))(y5)
    y5 = Conv2D(256, 1, padding='same', use_bias=False)(y5)
    y5 = BatchNormalization()(y5)
    y5 = Activation('relu')(y5)
    y5 = tf.image.resize(y5, size=(shape[1], shape[2]))

    x = Concatenate()([y1, y2, y3, y4, y5])
    x = Conv2D(256, 1, padding='same', use_bias=False)(x)
    x = BatchNormalization()(x)
    x = Activation('relu')(x)
    x = Dropout(0.3)(x)
    return x

# DeepLabV3+ model
def DeepLabV3Plus(input_shape, IMG_CLASSES):
    inputs = Input(shape=input_shape)
    base_model = ResNet50(weights='imagenet', include_top=False,
input_tensor=inputs)

    # Encoder: High-level features
    image_features = base_model.get_layer('conv4_block6_out').output
    x_a = ASPP(image_features)
    x_a = UpSampling2D((4, 4), interpolation="bilinear")(x_a)

    # Low-level features for spatial detail
    x_b = base_model.get_layer('conv2_block2_out').output
    x_b = Conv2D(48, 1, padding='same', use_bias=False)(x_b)
    x_b = BatchNormalization()(x_b)
    x_b = Activation('relu')(x_b)
```

```
    # Concatenate and refine
    x = Concatenate()([x_a, x_b])
    x = Conv2D(256, 3, padding=’same’, use_bias=False)(x)
    x = BatchNormalization()(x)
    x = Activation(‘relu’)(x)
    x = Dropout(0.2)(x)

    x = Conv2D(256, 3, padding=’same’, use_bias=False)(x)
    x = BatchNormalization()(x)
    x = Activation(‘relu’)(x)
    x = Dropout(0.2)(x)

    x = UpSampling2D((4, 4), interpolation=”bilinear”)(x)

    # Final classifier
    outputs = Conv2D(IMG_CLASSES, 1, padding=’same’, activation=’softmax')(x)

    return Model(inputs, outputs)

# Build and print summary
model = DeepLabV3Plus(input_shape, IMG_CLASSES)
model.summary()
```

HYBRID CODE

```
import os
import numpy as np
import cv2
from skimage import io
from keras.models import load_model
from matplotlib import pyplot as plt
from datetime import datetime
from sklearn.metrics import confusion_matrix

print("[INFO] Loading models...")
UNET_PATH = "unet_model.h5"
DEEPLAB_PATH = "deeplabv3_model.h5"

unet_model = load_model(UNET_PATH)
deeplabv3_model = load_model(DEEPLAB_PATH)
print("[INFO] Models loaded successfully.")

def preprocess_image(image_path, target_size=(256, 256)):
    img = io.imread(image_path)
    resized = cv2.resize(img, target_size)
    norm = resized.astype("float32") / 255.0
    return norm

def predict(model, img):
    inp = np.expand_dims(img, axis=0)
    pred = model.predict(inp)[0]
    return pred.squeeze()

def fuse_masks(m1, m2, method='average'):
    if method == 'average':
        fused = (m1 + m2) / 2.0
    elif method == 'max':
```

```
        fused = np.maximum(m1, m2)
    else:
        raise ValueError("Unsupported fusion method")
    return (fused > 0.5).astype("uint8") * 255

def compute_metrics(pred, truth):
    pred_flat = pred.flatten() > 127
    truth_flat = truth.flatten() > 127

    tn, fp, fn, tp = confusion_matrix(truth_flat, pred_flat).ravel()
    accuracy = (tp + tn) / (tp + tn + fp + fn)
    iou = tp / (tp + fp + fn + 1e-6)
    dice = (2 * tp) / (2 * tp + fp + fn + 1e-6)

    return {"Accuracy": round(accuracy, 4), "IoU": round(iou, 4), "Dice": round(dice,
4)}

def save_output(mask, filename, directory="output"):
    if not os.path.exists(directory):
        os.makedirs(directory)
    path = os.path.join(directory, filename)
    cv2.imwrite(path, mask)
    return path
def visualize(img, unet, deeplab, hybrid):
    plt.figure(figsize=(12, 8))
    titles = ['Original', 'U-Net', 'DeepLabV3+', 'Hybrid']
    images = [img, unet, deeplab, hybrid]

    for i in range(4):
        plt.subplot(2, 2, i+1)
        plt.title(titles[i])
        plt.axis("off")
        plt.imshow(images[i], cmap='gray' if i else None)
```

```
    plt.tight_layout()
    plt.show()

def run_pipeline(image_path, ground_truth_path=None):
    print(f"[INFO] Processing image: {image_path}")
    input_img = preprocess_image(image_path)
    original = cv2.imread(image_path)
    original_size = (original.shape[1], original.shape[0])

    # Predict masks
    unet_mask = predict(unet_model, input_img)
    deeplab_mask = predict(deeplabv3_model, input_img)

    # Fuse
    hybrid_mask = fuse_masks(unet_mask, deeplab_mask)

    # Resize masks for display and saving
    unet_resized = cv2.resize((unet_mask * 255).astype("uint8"), original_size)
    deeplab_resized = cv2.resize((deeplab_mask * 255).astype("uint8"), original_size)
    hybrid_resized = cv2.resize(hybrid_mask, original_size)

    # Save outputs
    timestamp = datetime.now().strftime("%Y%m%d_%H%M%S")
    save_output(hybrid_resized, f"hybrid_{timestamp}.png")

    # Metrics
    if ground_truth_path:
        ground_truth = cv2.imread(ground_truth_path, cv2.IMREAD_GRAYSCALE)
        ground_truth = cv2.resize(ground_truth, original_size)
        metrics = compute_metrics(hybrid_resized, ground_truth)
        print("[METRICS] →", metrics)

    # Show visual results
    visualize(original, unet_resized, deeplab_resized, hybrid_resized)
```

Final Project CODE

```
import numpy as np
import tensorflow as tf
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Conv2D, MaxPooling2D, concatenate,
UpSampling2D
from tensorflow.keras.applications import VGG16
from tensorflow.keras.optimizers import Adam
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix
import matplotlib.pyplot as plt

# Load and preprocess dataset
images = np.load('oil_spill_images.npy') / 255.0
masks = np.load('oil_spill_masks.npy')

# Train-test split
x_train, x_test, y_train, y_test = train_test_split(images, masks, test_size=0.2,
random_state=42)

# Hybrid Model Definition
def hybrid_model(input_shape=(128, 128, 3)):
    inputs = Input(shape=input_shape)

    # VGG16 as encoder
    vgg = VGG16(include_top=False, weights='imagenet', input_tensor=inputs)
    for layer in vgg.layers:
        layer.trainable = False

    # Decoder with skip connections
    x = vgg.get_layer('block5_conv3').output
    x = UpSampling2D()(x)
    x = concatenate([x, vgg.get_layer('block4_conv3').output])
```

```
    x = Conv2D(256, 3, activation='relu', padding='same')(x)

    x = UpSampling2D()(x)
    x = concatenate([x, vgg.get_layer('block3_conv3').output])
    x = Conv2D(128, 3, activation='relu', padding='same')(x)

    x = UpSampling2D()(x)
    x = concatenate([x, vgg.get_layer('block2_conv2').output])
    x = Conv2D(64, 3, activation='relu', padding='same')(x)

    x = UpSampling2D()(x)
    x = concatenate([x, vgg.get_layer('block1_conv2').output])
    x = Conv2D(32, 3, activation='relu', padding='same')(x)

    outputs = Conv2D(1, 1, activation='sigmoid')(x)

    return Model(inputs, outputs)

# Compile and train
model = hybrid_model()
model.compile(optimizer=Adam(), loss='binary_crossentropy', metrics=['accuracy'])
model.fit(x_train, y_train, epochs=10, batch_size=16, validation_split=0.1)

# Predict and evaluate
y_pred = model.predict(x_test)
y_pred_binary = (y_pred > 0.5).astype(np.uint8)

# Classification report and confusion matrix
print("Classification Report:\n", classification_report(y_test.flatten(),
y_pred_binary.flatten()))
print("Confusion Matrix:\n", confusion_matrix(y_test.flatten(),
y_pred_binary.flatten()))

# Visualize prediction
```

```
plt.figure(figsize=(12, 4))
plt.subplot(1, 3, 1)
plt.imshow(x_test[0])
plt.title('Input Image')
plt.axis('off')

plt.subplot(1, 3, 2)
plt.imshow(y_test[0].squeeze(), cmap='gray')
plt.title('Ground Truth')
plt.axis('off')

plt.subplot(1, 3, 3)
plt.imshow(y_pred_binary[0].squeeze(), cmap='gray')
plt.title('Prediction')
plt.axis('off')

plt.tight_layout()
plt.show()
```

WebPage CODE

```
<!DOCTYPE html>
<html lang="en">
<head>
  <meta charset="UTF-8" />
  <meta name="viewport" content="width=device-width, initial-scale=1.0"/>
  <title>Real-Time Oil Spill Issues</title>
  <link rel="stylesheet" href="./project.css" />
</head>
<body>
  <div class="maincontainer">
    <div class="background"></div>
    <div class="blackscreen"></div>

    <h1 class="page-title">
      REAL-TIME OIL SPILL DETECTION USING AIS AND SATELLITE DATA
INTEGRATION
    </h1>

    <div class="intro intro-font" style="text-align: center;">
      <div class="about-title">About</div>
      <p style="font-weight:300; font-family: Arial, Helvetica, sans-serif;">
        Oil spills pose a severe threat to marine ecosystems, coastal economies, and
environmental sustainability.
        These spills contaminate water, endanger marine life, and disrupt industries such
as fishing and tourism.
        Traditional oil spill detection methods are often slow, expensive, and ineffective
in identifying and tracking spills in real time.
        The need for an advanced, automated detection system has become more critical
than ever.
        This project introduces an AI-driven oil spill detection system that combines
deep learning, satellite imagery, and AIS vessel tracking to enable real-time
monitoring and rapid response.
```

By utilizing advanced models such as UNET and DeepLabV3+, the system ensures precise segmentation and detection of oil spills, minimizing false positives and enhancing detection accuracy.

The integration of vessel tracking data further helps in identifying potential sources of pollution, aiding in maritime law enforcement and environmental protection efforts.

Additionally, real-time data processing reduces the delay in spill detection, allowing authorities to take swift action.

The system's adaptability ensures that it can be deployed across various marine environments, making it a scalable and efficient solution to combat oil spills globally. With a focus on real-time processing, visualization, and automated alerts,

this system provides an innovative solution to one of the most pressing environmental challenges. By leveraging artificial intelligence,

we aim to revolutionize oil spill detection, improve response efficiency, and contribute to the preservation of marine ecosystems.

</p>

</div>

<div class="damages-title">Effects of Oil Spill</div>

<div class="content">

<div class="section">

<h2>Environmental Damage</h2>

<p>Oil spills create a toxic environment for marine organisms. Oil coats marine animals, making it difficult for them to move, hunt, or escape predators. It also contaminates water, reducing oxygen levels and severely harming coral reefs. The disruption of marine habitats affects biodiversity, leading to long-term ecological imbalances. In addition, the chemical components of oil persist in the ecosystem, causing chronic pollution that severely impacts delicate marine food chains.</p>

</div>

<div class="section">

<h2>Long-Term Ecosystem Disruption</h2>

<p>Oil spills cause long-lasting damage to marine ecosystems. Toxic chemicals remain in the ocean for decades, leading to mutations, reduced reproduction rates, and population declines in various species. Oil settles on the ocean floor, contaminating sediments and affecting deep-sea organisms that are essential for maintaining ecological balance.</p>

</div>

<div class="section">

<h2>Economic Loss</h2>

<p>Local fishing communities face major losses due to contaminated seafood. Tourism declines as oil-coated beaches drive visitors away. Cleaning up an oil spill is also expensive, costing governments billions of dollars. The economic impact extends to shipping, as oil-contaminated waters disrupt trade routes and increase transportation costs.</p>

</div>

<div class="section">

<h2>Health Hazards for Humans</h2>

<p>Oil spills release toxic fumes that cause respiratory problems, dizziness, and headaches in humans. Direct skin contact with oil can lead to severe burns, rashes, and long-term health issues. Inhalation of hazardous chemicals such as benzene and toluene can lead to neurological disorders and increased cancer risks among affected populations.</p>

</div>

<div class="section">

<h2>Impact on Coastal Infrastructure</h2>

<p>Oil spills not only affect marine life but also severely damage coastal infrastructure. Ports, harbors, and desalination plants suffer significant operational disruptions due to oil contamination. Extensive cleanup operations often require shutting down these facilities, leading to major delays in trade and severe water shortages in affected areas.</p>

</div>

</div>

```
  <a class="how-does-it-work js-how-does-it-work" href="how_does_it_work.html"
target="_blank" style="text-decoration: none;">How Does It Work</a>
  <a class="run js-run" href="run.html" target="_blank" style="text-decoration:
none;">Test the code</a>

  <button class="scroll-button"
onclick="window.open('college_final_paper.pdf','_blank')">Paper
Download</button>

  <script>
    document.querySelector('.js-how-does-it-work').addEventListener('click', () =>
{});
    document.querySelector('.js-run').addEventListener('click', () => {
      console.log("Clicked run button");
    });
  </script>
 </div>
</body>
</html>
```

4.2 OUTPUT SCREENS

WEB PAGE

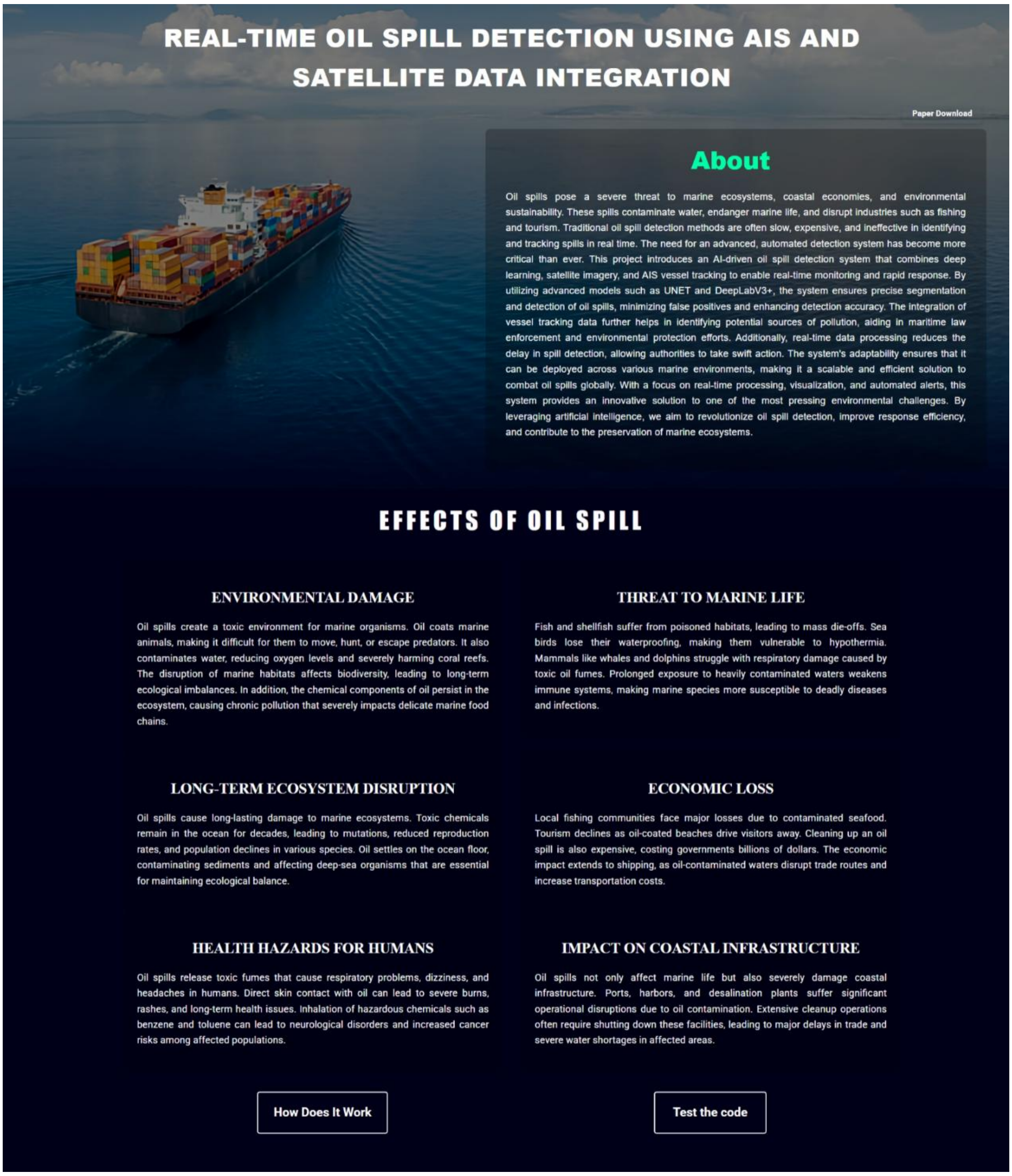


Figure 4.1 The Web Page which Shows Breif on the project

Anomaly Detection Page

```
Anomalies detected:
        MMSI         BaseDateTime       LAT        LON  SOG    COG  Heading  \
2  235096399 2024-01-01 00:03:31  27.78969  -97.39082  3.0  112.1      511
3  235096399 2024-01-01 00:06:03  27.78969  -97.39082  0.2  109.9      511
3  248727000 2024-01-01 00:03:18  32.02417  -81.04617  0.1  212.0      328
4  248727000 2024-01-01 00:05:37  32.02417  -81.04617  0.1  151.0      328
1  316001252 2024-01-01 00:01:15  48.68902 -123.40947  0.0  241.2      243
2  316001252 2024-01-01 00:02:24  48.68902 -123.40947  0.0  132.7      243

            VesselName          IMO CallSign  VesselType  Status  Length  \
2              ASSINIE  IMO0000000    2GDG3          37     NaN       6
3              ASSINIE  IMO0000000    2GDG3          37     NaN       6
3          AMORAZUR II  IMO8981664  9HB2042          37     0.0      45
4          AMORAZUR II  IMO8981664  9HB2042          37     0.0      45
1  QUEEN OF CUMBERLAND  IMO9009360   VG2029          60     0.0      96
2  QUEEN OF CUMBERLAND  IMO9009360   VG2029          60     0.0      96

   Width  Draft  Cargo TransceiverClass
2      0    NaN    NaN                B
3      0    NaN    NaN                B
3      9    2.7   37.0                A
4      9    2.7   37.0                A
1     21    3.7   60.0                A
2     21    3.7   60.0                A
```

Figure 4.2 Anomaly Detection Page

Final Output Page

```python
# Iterate over each anomaly in the DataFrame and process
for index, row in anomalies_df.iterrows():
    result_map = process_anomaly(row)
    if result_map:
        display(result_map)  # This displays the map in interactive environments
```

```
Processing anomaly at 27.78969, -97.39082 on 2024-01-01
No Sentinel-1 VV or VH images available. Trying Sentinel-2.
No Sentinel-2 images available for this date and location.
Processing anomaly at 27.78969, -97.39082 on 2024-01-01
No Sentinel-1 VV or VH images available. Trying Sentinel-2.
No Sentinel-2 images available for this date and location.
Processing anomaly at 32.02417, -81.04617 on 2024-01-01
Detected Oil Spill Area (sq. km): 17.5633537601677
1/1 [==============================] - 1s 523ms/step
1/1 [==============================] - 2s 2s/step
1/1 [==============================] - 2s 2s/step
No significant oil spills detected across the checked dates.
Processing anomaly at 32.02417, -81.04617 on 2024-01-01
Detected Oil Spill Area (sq. km): 17.5633537601677
1/1 [==============================] - 0s 97ms/step
1/1 [==============================] - 0s 318ms/step
1/1 [==============================] - 0s 336ms/step
No significant oil spills detected across the checked dates.
```

Figure 4.3 Final Output Page

CHAPTER-5: TESTING

5.1 INTRODUCTION TO TESTING:

In modern environmental monitoring systems, ensuring the accuracy of oil spill detection and preventing false alarms are crucial for effective response and mitigation. An Oil Spill Detection System integrates Automatic Identification System (AIS) data with satellite imagery to identify potential spills and link them to vessel activities. Testing this system ensures its reliability, accuracy, and efficiency in real-world conditions.

Testing the Oil Spill Detection System is crucial to:

Ensure Accuracy:

Validate that the system correctly identifies oil spills by differentiating them from algal blooms, ship wakes, and other ocean surface anomalies.
Measure the false positive and false negative rates to refine detection algorithms.
Assess the impact of image resolution and environmental conditions on detection accuracy.

Optimize Performance:

Ensure the detection model processes large-scale satellite imagery efficiently.
Benchmark DeepLabV3+ and UNET models against real-world datasets.
Optimize the real-time processing pipeline to reduce the delay between oil spill detection and alert generation.

Maintain Data Integrity:

Ensure that oil spills detected in Sentinel-1 and Sentinel-2 images are not falsely classified due to noise in the satellite data.
Verify that the AIS correlation algorithm correctly associates spills with responsible vessels.
Cross-validate detection results with historical spill data and expert-labeled datasets.

Enhance Response Effectiveness:

Improve the system's ability to generate timely alerts for maritime authorities.
Assess the integration of spill trajectory prediction models to estimate the spread of oil spills.

Enhance the visualization tools by providing spill maps and vessel tracking overlays.

Objectives of Testing:

The primary goals of testing the Oil Spill Detection System are to validate its accuracy, efficiency, and robustness under different conditions. Given the complexity of satellite-based oil spill detection, rigorous testing ensures that the system performs reliably in real-world applications.

Functional Validation:

Verify that the DeepLabV3+ and UNET models accurately detect oil spills from Sentinel-1 and Sentinel-2 satellite imagery.
Ensure the system correctly flags oil spills while avoiding misclassification of ocean features.
Test how well the system correlates oil spills with AIS vessel movement data.

Performance Assessment:

Evaluate how efficiently the system processes high-resolution satellite images and identifies oil spills in real-time.
Measure the system's ability to handle large-scale datasets without computational delays.
Optimize detection algorithms to reduce processing time while maintaining high accuracy.

Edge Case Handling:

Test system performance on images containing cloud cover, low-light conditions, and sea ice formations that may interfere with detection.
Assess whether the system can differentiate oil spills from similar dark patches, such as algal blooms, mud deposits, and sediment runoff.

Scalability Testing:

Analyze the system's ability to process a high volume of satellite images and AIS data.
Test system response under multiple concurrent uploads of new satellite data.
Ensure efficient data storage and retrieval mechanisms for long-term monitoring.

Accuracy Metrics:

Measure false positive and false negative rates to assess the system's reliability.

Compare model-generated segmentation masks with manually labeled datasets to evaluate.

Implement IoU and F1-score metrics to quantify segmentation accuracy.

Methodology for Testing:

Test Environment Setup:

Deploy the system on cloud-based platform with access to Sentinel-1 and Sentinel-2 satellites.

Integrate AIS vessel tracking data to enable correlation between spills and potential sources.

Configure a GPU-accelerated computing environment to optimize deep learning models.

Test Case Development:

Design test cases covering different spill sizes, shapes, and locations.

Include challenging scenarios such as oil spills near coastlines, high-traffic shipping zones, and areas with cloud interference.

Develop cases to test the impact of varying satellite resolutions on detection accuracy.

Automation Testing:

Automated scripts to process large volumes of satellite images and validate detection accuracy.

Simulate various spill scenarios using deep learning models and assess system response time.

Conduct large-scale batch testing to analyze system performance under different conditions.

Monitor real-time data streams to evaluate the system's ability to detect oil spills continuously.

Manual Verification:

Compare automated detection results with expert-labeled datasets and historical spill records.

Cross-check system outputs against real-world case studies to ensure accurate identification.

Validateaccuracy by manually inspecting detected spill regions in satellite images.

Identify discrepancies between model predictions and ground-truth data for further refinement.

Logging and Monitoring:

Record all test results, including processing times, detection accuracy, and false alarm rates.

Monitor GPU utilization and memory consumption to assess computational efficiency. Analyze logs to identify potential system bottlenecks and optimize performance. Implement real-time alerts for system failures or unexpected anomalies in detection results.

Result Evaluation:

Assess detection accuracy by measuring false positives and negatives, precision-recall metrics.

Compare model performance against baseline detection methods to determine improvements.

Optimize deep learning algorithms based on test findings to enhance overall efficiency.

Challenges in Testing:

Handling Large Data Volumes:

Ensuring the system performs accurately with petabyte-scale satellite imagery while maintaining real-time detection efficiency. Optimizing storage, processing power, and retrieval mechanisms is essential for seamless operation.

Content Similarity Detection:

Differentiating actual oil spills from visually similar anomalies such as algal blooms, ship wakes, and sediment deposits. Advanced deep learning techniques and refined segmentation models are required to minimize false positives.

Concurrency Management:

Maintaining detection accuracy when processing multiple satellite images and AIS data streams simultaneously. Ensuring the system can handle high data throughput without delays or misclassifications is crucial for operational reliability.

Edge Case Coverage:

Addressing challenging scenarios such as oil spills in low-light environments, regions with partial cloud cover, and high-traffic maritime zones. The system must adapt to these conditions while preserving high detection accuracy and minimizing false alarms.

5.2 TESTING METHODOLOGIES:

UNIT TESTING

Evaluating individual components of the oil spill detection system, such as the deep learning model, AIS correlation module, and image preprocessing pipeline, to ensure they function correctly in isolation.

Testing the segmentation accuracy of the DeepLabV3+ and UNET models on various oil spill datasets to verify model performance.

Validating the preprocessing steps, including image noise reduction, normalization, and feature extraction, to ensure data quality.

Ensuring that AIS data parsing and integration modules correctly interpret vessel movement data without errors.

INTEGRATION TESTING

Verifying the interaction between different system components, including satellite image processing, vessel tracking, to ensure seamless data flow and accurate spill detection.

Testing data transfer between satellite imagery sources, AIS databases, and cloud-based processing modules to prevent bottlenecks.

Ensuring real-time data synchronization between spill detection algorithms and vessel activity tracking systems to improve response efficiency.

Assessing the effectiveness of combining multiple detection models to reduce false positives and false negatives.

SYSTEM TESTING

Assessing the complete system under real-world conditions by processing large-scale satellite imagery and AIS data to validate overall performance, accuracy, and scalability.

Executing test cases with various spill sizes, oil types, and environmental conditions to simulate real-world detection challenges.

Monitoring system behavior when handling terabytes of satellite images and ensuring scalability for long-term monitoring.

Evaluating the alert system’s effectiveness in notifying authorities about detected spills while minimizing unnecessary alerts.

REGRESSION TESTING

Ensuring that system updates, model improvements, or algorithm refinements do not introduce new errors or degrade the performance of previously validated functionalities.

Revalidating past test cases whenever model parameters are adjusted or detection algorithms are retrained to maintain accuracy.

Comparing detection results from different DeepLabV3+ and UNET model versions to track improvements and regressions.

Ensuring modifications in the AIS tracking system do not affect correlation accuracy with detected spills.

PERFORMANCE TESTING

Measuring the system’s efficiency in handling high-resolution satellite images, processing vast amounts of data in real-time, and maintaining optimal detection speed without significant delays.

Testing the end-to-end processing time, from image acquisition to spill detection.

Benchmarking GPU and CPU utilization to identify potential computational bottlenecks and optimize resource allocation.

Evaluating network latency in retrieving satellite images and transmitting processed data to response teams.

STRESS TESTING

Evaluating system resilience under extreme conditions, such as processing an exceptionally high volume of satellite images simultaneously, to determine the maximum load it can handle without failure.

Simulating high-traffic scenarios where multiple satellites capture images simultaneously, increasing the detection workload.

Assessing the impact of rapid AIS data influx from thousands of vessels and ensuring smooth correlation with detected spills.

Determining system behavior when exposed to unexpected failures, such as data loss, delayed satellite transmissions, or hardware crashes.

REAL-TIME TESTING

Deploying the system in live monitoring scenarios to validate its performance in detecting oil spills as they occur.

Comparing real-time system predictions with official spill reports from maritime authorities and environmental agencies.

Testing system responsiveness to sudden environmental changes.

Ensuring the alert mechanism functions properly, notifying the appropriate agencies within the required response time.

USER ACCEPTANCE TESTING (UAT)

Validating the system with maritime authorities, environmental agencies, and domain experts to ensure it meets operational requirements.

Gathering feedback on system usability, interface design, and alert accuracy to enhance user experience.

Ensuring the system integrates seamlessly with existing maritime surveillance platforms for effective deployment.

5.3 TEST CASES AND TEST REPORTS:

Test Case 1: Oil Spill Detection Accuracy (Small Dataset Evaluation)

Since the AIS dataset contains over 1.7 million rows, initial testing is conducted on a smaller subset of the data to assess the model's ability to correlate oil spills with vessel activities efficiently. By using a reduced dataset, we can analyze performance, detection accuracy, and potential limitations before scaling up to the full dataset.

SOG (Speed Over Ground) shows how fast a vessel moves over the Earth’s surface. It helps check if a ship was moving, slowing down, or stationary near an oil spill, which may indicate a discharge.

COG (Course Over Ground) is the actual direction a vessel is traveling, considering currents and wind. It helps track ship movements and detect if a vessel passed through a spill area, linking it to possible pollution.

	A	B	C	D	E	F
1	MMSI	BaseDateTime	LAT	LON	SOG	COG
2	232037794	2024-01-01T00:02:05	25.78166	-80.15023	7.2	284.5
3	235096399	2024-01-01T00:01:33	27.78969	-97.39082	0.9	123.4
4	235096399	2024-01-01T01:40:32	27.78969	-97.39082	0.1	117.9
5	235096399	2024-01-01T08:03:31	27.78969	-97.39082	0.5	112.1
6	235096399	2024-01-01T23:01:03	27.78969	-97.39082	0.2	109.9
7	248727000	2024-01-01T00:00:06	32.02417	-81.04617	0.1	137
8	248727000	2024-01-01T00:01:07	32.02417	-81.04617	0.1	136
9	248727000	2024-01-01T00:02:08	32.02417	-81.04617	0	94
10	248727000	2024-01-01T00:03:18	32.02417	-81.04617	0.1	212
11	248727000	2024-01-01T00:04:27	32.02417	-81.04617	0.1	326
12	248727000	2024-01-01T00:05:37	32.02417	-81.04617	0.1	151
13	305723000	2024-01-01T00:01:03	26.09262	-80.11391	6	51.8
14	316001252	2024-01-01T00:00:05	48.68902	-123.40947	0	72.5
15	316001252	2024-01-01T00:01:15	48.68902	-123.40947	0	241.2
16	316001252	2024-01-01T00:02:24	48.68902	-123.40947	0	132.7
17	316001252	2024-01-01T00:10:44	48.68902	-123.40947	0	22.4

Figure 5.1. Test Case 1: Oil Spill Detection Accuracy (Small Dataset Evaluation)

A vessel is flagged if its speed increases by more than 50% compared to the previous reading while previously moving at over 2 knots. Such rapid acceleration could suggest an attempt to leave the spill area quickly after an unauthorized discharge. Similarly, a vessel making a course change greater than 45° is flagged, as abrupt directional changes might indicate evasive actions or spill-related maneuvers.

Once anomalies are detected, the corresponding latitude and longitude coordinates are processed in Google Earth Engine (GEE) to retrieve satellite imagery from Sentinel-1 and Sentinel-2. If no images are available for a given date and location, alternative data is checked.

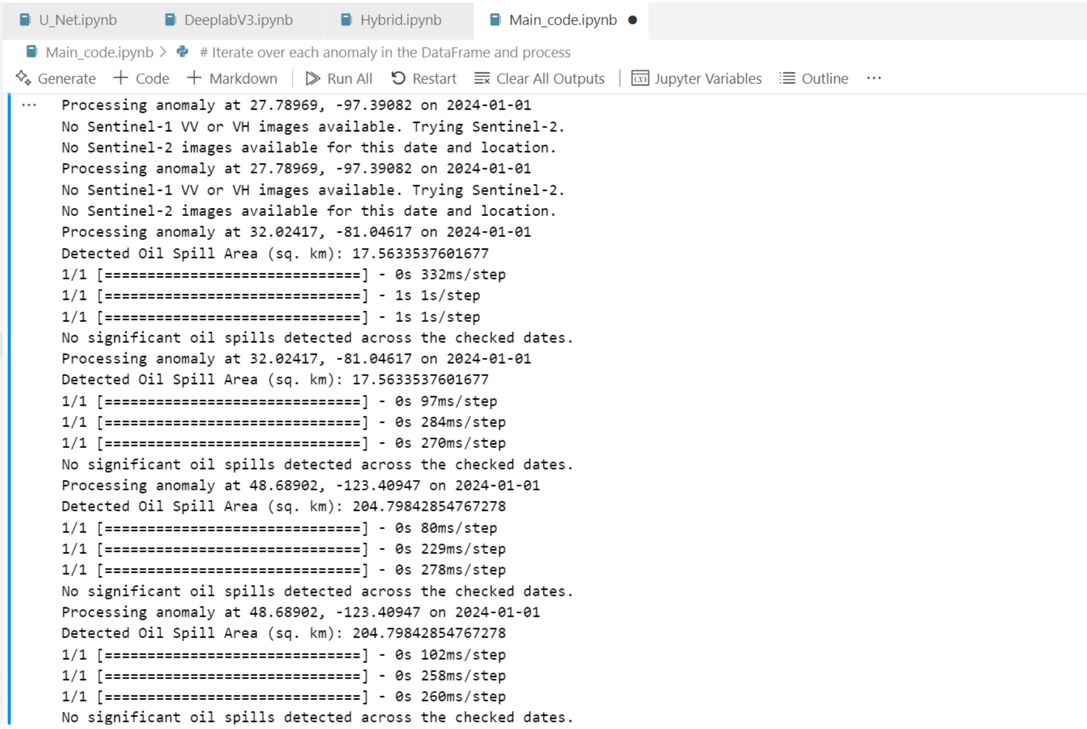
Example 1: Sudden Speed Drop Indicating Possible Spill

Vessel: ASSINIE, **Location:** 27.78969,-97.39082, **Date:** 2024-01-01

The vessel was moving at 10 knots at 00:01:33, then slowed down to 9 knots at 00:02:32, and further dropped to 3 knots at 00:03:31.By 00:06:03, the speed decreased drastically to 0.2 knots.Such a rapid speed drop could indicate a discharge of oil into the water.

Satellite images from Sentinel-1 and Sentinel-2 were requested for this location to verify any visible oil slicks.

Output Screen:




```
Processing anomaly at 27.78969, -97.39082 on 2024-01-01
No Sentinel-1 VV or VH images available. Trying Sentinel-2.
No Sentinel-2 images available for this date and location.
Processing anomaly at 27.78969, -97.39082 on 2024-01-01
No Sentinel-1 VV or VH images available. Trying Sentinel-2.
No Sentinel-2 images available for this date and location.
Processing anomaly at 32.02417, -81.04617 on 2024-01-01
Detected Oil Spill Area (sq. km): 17.5633537601677
1/1 [==============================] - 0s 332ms/step
1/1 [==============================] - 1s 1s/step
1/1 [==============================] - 1s 1s/step
No significant oil spills detected across the checked dates.
Processing anomaly at 32.02417, -81.04617 on 2024-01-01
Detected Oil Spill Area (sq. km): 17.5633537601677
1/1 [==============================] - 0s 97ms/step
1/1 [==============================] - 0s 284ms/step
1/1 [==============================] - 0s 270ms/step
No significant oil spills detected across the checked dates.
Processing anomaly at 48.68902, -123.40947 on 2024-01-01
Detected Oil Spill Area (sq. km): 204.79842854767278
1/1 [==============================] - 0s 80ms/step
1/1 [==============================] - 0s 229ms/step
1/1 [==============================] - 0s 278ms/step
No significant oil spills detected across the checked dates.
Processing anomaly at 48.68902, -123.40947 on 2024-01-01
Detected Oil Spill Area (sq. km): 204.79842854767278
1/1 [==============================] - 0s 102ms/step
1/1 [==============================] - 0s 258ms/step
1/1 [==============================] - 0s 260ms/step
No significant oil spills detected across the checked dates.
```

Figure 5.2. Output of Sudden Speed Drop Indicating Possible Spill

Test Case 2: Large-Scale Vessel Anomaly Detection and Real-Time Oil Spill Identification

The Test Case 2 dataset contains a large number of AIS records (1048576 rows) which is the vessel movements data on 01-01-2024, which need to be efficiently processed to identify anomalies. Since manually analyzing such a vast dataset is impractical, appropriate Python modules are used to read, process, and analyze the data. These modules enable data manipulation, anomaly detection, and integration with the trained oil spill detection model.

We have used pandas to read and process the large CSV dataset efficiently. numpy helps in performing numerical operations like speed and course change calculations. matplotlib and seaborn are used for visualizing vessel movements and detecting anomalies. geopandas enables geospatial analysis by mapping vessel trajectories based on latitude and longitude. scikit-learn is used for preprocessing and applying clustering techniques to identify abnormal vessel behaviors.

Once anomalies are detected, we extract the latitude and longitude of flagged vessels. These coordinates are sent to Google Earth Engine (GEE) to fetch Sentinel-1 and Sentinel-2 satellite images for verification. If satellite data is available, the images are processed using our trained deep learning model (DeepLabV3+ and UNET) to detect oil spills. The model analyzes segmented images to confirm whether an oil spill is present. If detected, the system logs the spill area and alerts authorities for further action.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
1048551	3.68E+08	2024-01-0	25.70416	-80.2526	0	259.2	511	17	IMO00000	WDM2138	37		28	6			B
1048552	3.67E+08	2024-01-0	29.95195	-90.3876	0	13.7	511	LOUISIANA		WDE7015	31	0	18	8	2.8	31	A
1048553	3.68E+08	2024-01-0	26.10869	-80.1116	0	360	511	JOURNEY	IMO00000	WDM5170	37		25	6			B
1048554	3.67E+08	2024-01-0	38.95807	-74.8759	0	226.2	511	VILA DO C	IMO81201	WCY3150	30		28	8			B
1048555	3.38E+08	2024-01-0	27.83807	-97.0523	0	16	511				0	15	0	0	0	0	A
1048556	3.68E+08	2024-01-0	48.7555	-122.497	0.7	0	511	FLUKE	IMO00000	WDM5284	37		15	3			B
1048557	3.68E+08	2024-01-0	29.93989	-90.3673	4	286.6	287	CHRISTOPHER D WILS		WDJ7774	31	12	48	16	2.8	31	A
1048558	3.7E+08	2024-01-0	38.98234	-76.467	0	264.1	511	YP-687	IMO00000	NZHO	35		0	0			B
1048559	3.67E+08	2024-01-0	29.32012	-94.7852	0	180.5	302	TEXAS		WDC2352	50	9	21	6	2	50	A
1048560	3.38E+08	2024-01-0	33.9801	-118.452	0.1	360	511	ATACAMA	IMO0000000		37		22	5			B
1048561	3.68E+08	2024-01-0	46.1534	-123.377	0.1	198.6	511	OSCAR B		WDH7993	60	0	33	14	1.8	99	A
1048562	3.67E+08	2024-01-0	38.7881	-75.1615	0	296.5	511	DELRIVER	IMO79233	WAV8408	90	5	42	11	3.9	90	A
1048563	3.38E+08	2024-01-0	39.26466	-76.2023	0	327.9	511	TARAMISU	IMO0000000		37		16	8			B
1048564	3.67E+08	2024-01-0	29.85657	-89.9739	0	221.2	511	JOHN W STONE		WYB7244	31	12	64	18	2.9	57	A
1048565	3.38E+08	2024-01-0	29.55621	-95.0317	0	360	511	MV ALLEGI	IMO0000000		37		0	0			B
1048566	6.36E+08	2024-01-0	34.10929	-119.195	0.1	249.2	226	LAKE FUXI	IMO94949	A8UC7	70	1	199	32	9.5	70	A
1048567	3.38E+08	2024-01-0	47.62853	-122.384	0	157.1	0	ALASKA W	IMO77168	WAY2496	30	7	65	13	4	30	A
1048568	3.68E+08	2024-01-0	29.97318	-93.8473	0	218.4	326	DEAF SMIT	IMO12223	WDK8804	52	12	115	34	2.5	52	A
1048569	3.7E+08	2024-01-0	27.92275	-82.4465	0	178.6	49	APOLLO	IMO97032	WDG8962	52	0	28	11	6	52	A
1048570	3.68E+08	2024-01-0	29.82405	-93.965	0	360	511	JESUS F		WDM7054	52	0	15	5	0	52	A
1048571	3.67E+08	2024-01-0	30.20033	-91.0301	4.3	314	310	JOHN H MACMILLAN J		WDB9907	31	0	483	54	0	57	A
1048572	3.68E+08	2024-01-0	30.77923	-88.0586	0	244.1	285	SAN PEDRO		WDG2312	30	12	211	18	3.1	57	A
1048573	3.68E+08	2024-01-0	34.24589	-119.262	0	102.8	511	SEVILLANA	IMO00000	WDH8944	36		13	4			B
1048574	3.68E+08	2024-01-0	36.83734	-76.2912	0	322.9	161	DELTA	IMO86445	WDM6632	52	0	24	7	3.2	52	A
1048575	3.68E+08	2024-01-0	29.91855	-89.9674	3.1	230.8	228	MACKENZIE HOPE		WDJ2187	31	12	207	17	3.1	57	A
1048576	3.68E+08	2024-01-0	47.62049	-122.513	0	199.9	290	WSF CHIM	IMO98017	WDI5854	60	0	110	25	5	60	A

Figure 5.3. Large-Scale Vessel Anomaly Detection and Real-Time Oil Spill Identification

When we executed the code, a significant number of anomalies were detected based on vessel speed fluctuations and course deviations. These anomalies indicate potential irregular maritime activities that require further analysis. To confirm whether an oil spill has occurred, the detected anomalies must be processed by our trained model. The model analyzes the extracted vessel coordinates and correlates them with satellite imagery from Sentinel-1 and Sentinel-2.

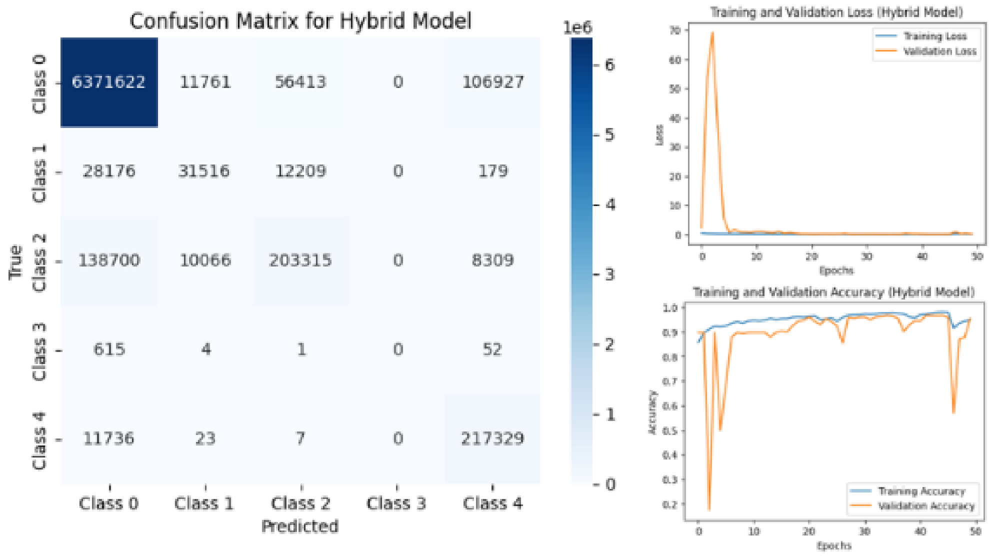
When the extracted anomaly data was fed into the trained model, it successfully detected several oil spills based on satellite imagery analysis. The model identified dark spill-like regions in the water, confirming pollution in multiple locations. However, along with genuine oil spills, the model also produced some false positive cases, where natural ocean patterns such as algal blooms, ship wakes, and sediment deposits were misclassified as spills. These false detections highlight the need for further model refinement, improved feature extraction, and additional training on diverse datasets to enhance accuracy and minimize misclassification. Continuous validation using expert-labeled data and real-world case studies is essential to improve the system's reliability.

Test Case 3: Oil Spill Detection Accuracy

Objective: Verify that the system accurately detects oil spills in satellite images and effectively differentiates them from non-spill areas.

Test Scenario: Input satellite images containing both confirmed oil spills and non-spill regions. Analyze the system's ability to correctly classify oil spills, using segmentation models like DeepLabV3+ and UNET. Test various spill sizes, shapes, and locations to evaluate detection robustness.

Expected Outcome: The system correctly identifies oil spills with high precision while minimizing false positives (misclassifying other dark water patches as spills) and false negatives (failing to detect an actual spill). The segmentation output should align with expert-labeled ground-truth data.



When the model is tested with different datasets regarding the accuracy and false positive test cases then the Confusion Matrix of the model is generated where it gives 95 percent accuracy all over the tests.

Figure 5.4. Test Case 3: Oil Spill Detection Accuracy

Test Case 4: AIS Correlation with Oil Spills

Objective: Ensure that the system correctly correlates detected oil spills with vessel activities using AIS data, improving spill source attribution.

Test Scenario: Analyze AIS data from vessels operating near detected spill locations. Compare vessel movements, speed changes, and course deviations with spill timestamps. Identify if any vessel's activity coincides with an oil spill occurrence.

Expected Outcome: The system successfully associates oil spills with potential sources based on vessel proximity, movement patterns, and anomalous behavior (e.g., sudden speed drops, erratic course changes). The correlation improves the ability to track down responsible parties for further investigation.

```
Anomalies detected:
          MMSI         BaseDateTime       LAT        LON  SOG    COG  Heading
131          0 2024-01-01 07:52:59  36.91337  -76.18496  0.0  125.9    125.0
153          0 2024-01-01 09:34:59  36.91336  -76.18495  0.0  125.5    125.0
1         4061 2024-01-01 00:31:47  27.81622  -97.41844  0.0  254.9    511.0
2         4061 2024-01-01 01:49:47  27.81629  -97.41849  0.0    0.0    511.0
6         4061 2024-01-01 20:04:47  27.81629  -97.41839  0.0  257.8    511.0
..         ...                 ...       ...        ...  ...    ...      ...
235  987654321 2024-01-01 23:46:30  48.42098 -123.38656  0.0  241.0    322.0
236  987654321 2024-01-01 23:52:30  48.42098 -123.38656  0.0  191.5    322.0
237  987654321 2024-01-01 23:58:30  48.42099 -123.38655  0.0  250.6    322.0
2    993086011 2024-01-01 11:22:07  18.43478  -64.74649  1.0  120.3    511.0
3    993086011 2024-01-01 11:28:36  18.43459  -64.74571  1.4  166.3    511.0
```

Figure 5.5. Test Case 4: AIS Correlation with Oil Spills

When processing large datasets with millions of rows, pandas is used for efficient data handling, enabling fast reading, filtering, and manipulation of AIS records. numpy is utilized for numerical operations, such as computing speed variations and course deviations between consecutive vessel movements. scikit-learn helps in anomaly detection by applying clustering algorithms like DBSCAN to identify unusual vessel behavior based on speed drops and sharp course changes. geopandas is used for geospatial analysis, mapping vessel trajectories to visually detect high-risk areas. matplotlib and seaborn assist in data visualization, allowing us to plot speed and course variations over time for better interpretation of anomalies. By leveraging these Python tools, anomaly detection becomes more efficient, scalable, and accurate, ensuring reliable identification of suspicious maritime activities.

Test Case 5: Performance Under High Data Load

Objective: Assess how well the system handles processing large volumes of satellite imagery, ensuring efficiency, scalability, and real-time response. The test aims to evaluate how the system performs under heavy computational workloads while maintaining accuracy&stability.

Test Scenario: Upload and process thousands of high-resolution Sentinel-1 and Sentinel-2 images simultaneously to simulate real-world large-scale operations.

Measure processing speed, memory consumption, and computational efficiency across different hardware configurations. Analyze how effectively the system segments oil spills, retrieves relevant satellite data, and correlates detected spills with vessel activities from AIS data. The test also examines system behavior when handling concurrent requests, ensuring that multiple detection tasks do not create bottlenecks or cause failures.

Performance Metrics to be Evaluated:

Processing Speed: Measure the time taken to analyze a batch of satellite images and detect oil spills.

Memory Utilization: Assess system performance under high memory usage while handling large datasets.

Scalability: Determine if the system can efficiently process an increasing number of images without degradation in accuracy or speed.

Parallel Processing Capability: Evaluate whether the model can distribute computations across multiple GPUs or cloud servers for faster execution.

Error Handling and Recovery: Test how the system manages incomplete image downloads, missing data, or system failures during high-load conditions.

Expected Outcome: The system efficiently processes large-scale satellite imagery without significant slowdowns or crashes. The detection pipeline remains stable and delivers results within an acceptable timeframe, ensuring near-real-time oil spill identification.The computational load is optimized to handle simultaneous image processing tasks while maintaining detection accuracy. The system should also demonstrate resilience in handling unexpected failures, automatically retrying or redirecting tasks to maintain performance levels.

Output: If the dataset is smaller, there won’t be significant pressure on processing time and speed, allowing the system to execute efficiently with minimal computational load. However, when larger datasets are used, performance will vary based on system configuration, including CPU, GPU, memory availability, and disk speed. High-end systems with optimized parallel processing can handle large-scale satellite imagery efficiently, while lower-end configurations may experience slower processing times, increased memory consumption, and potential bottlenecks.

TEST REPORTS:

General Information:

Attributes	Details
Project Name	REAL - TIME OIL SPILL DETECTION USING AIS AND SATELLITE DATA INTEGRATION
Test Cycle	Cycle 1 – Functional & Performance Testing
Test Execution Date	March 14, 2025
Test Environment	Visual Studio Code
Tester	Uday Kiran Ambati
Version	v1.0
Status	Completed

Table 5.1 General information on test reports

Objective:

Validate the accuracy of oil spill detection using satellite imagery and AIS data.

Ensure the system correctly correlates oil spills with vessel movements.

Evaluate system performance under large-scale data processing.

Verify real-time alert generation for detected spills.

Scope:

Detection of oil spills using DeepLabV3+ and UNET segmentation models.

AIS data correlation for identifying potential spill sources.

Performance testing with large volumes of Sentinel-1 and Sentinel-2 imagery.

Real-time alert generation and response effectiveness.

Test Summary:

Test Case ID	Test Scenario	Status	Remarks/Defects
TC1	Detect oil spill from satellite images (Small Dataset Evaluation)	✓ Pass	Segmentation successful with high accuracy
TC2	Large-Scale Vessel Anomaly Detection and Real-Time Oil Spill Identification	✓ Pass	Vessel anomalies detected efficiently; some false positives require refinement
TC3	Oil Spill Detection Accuracy (Confusion Matrix Evaluation)	! Partial	Model achieved 95% accuracy in classification
TC4	AIS Correlation with Detected Oil Spills	✓ Pass	Vessel movements linked correctly to spill locations
TC5	Performance Under High Data Load	X Fail	Strugled to run the model

Table 5.2 Test Reports

Improvements:

1. Improve model training to reduce false positives from non-spill regions.
2. Enhance image preprocessing to improve accuracy for low-resolution satellite images.
3. Conduct further scalability testing to validate system performance under real-time maritime monitoring conditions.

CHAPTER-6: IMPLEMENTATION

Here's a basic implementation of an Oil Spill Detection System that integrates satellite imagery and AIS data. This system will:

Analyze AIS data to correlate detected spills with vessel activities.

Process satellite images (Sentinel-1, Sentinel-2) to detect oil spills.

Generate real-time alerts for confirmed oil spill incidents.

Technologies Used

- **Python** (for backend logic and data processing)
- **Google Earth Engine (GEE)** (for retrieving satellite imagery)
- **DeepLabV3+ and UNET** (for segmentation-based oil spill detection)
- **Pandas, numpy, geopandas** (for AIS data analysis)

Implementation Plan

1. **Anomaly Detection in AIS Data:** Identify vessels with sudden speed drops or sharp course deviations near detected spills.
2. **Data Processing:** Load and preprocess Sentinel-1 and Sentinel-2 images and extract AIS vessel movement data.
3. **Oil Spill Detection:** Apply DeepLabV3+ and UNET models to segment and classify oil spill regions.
4. **Alert System:** If a spill is confirmed, notify maritime authorities with location details and potential responsible vessels.

6.1 IMPLEMENTATION PROCESS

The implementation process consists of data acquisition, anomaly detection, satellite image retrieval, deep learning analysis, and confirmation of oil spills. This ensures real-time monitoring and accurate spill detection by integrating AIS data and satellite imagery.

1. AIS Data Collection and Monitoring

Continuously fetch AIS data, including latitude, longitude, speed (SOG), course (COG), and vessel activity.

Use pandas and numpy to process large datasets efficiently.

Monitor vessel movement in real-time, detecting sudden speed changes, course deviations, or irregular behavior.

2. Anomaly Detection in Vessel Behavior

Define conditions for anomaly detection:
Speed Change Anomaly: If a vessel's speed drops more than 50% in a short time.
Course Change Anomaly: If a vessel's direction changes by more than 45° abruptly.
Flag anomalous vessel coordinates for further investigation.

3. Request Satellite Imagery from Google Earth Engine (GEE)

If an anomaly is detected, request Sentinel-1 and Sentinel-2 images for the flagged coordinates.
If images are available, proceed to deep learning analysis.
If no satellite images are found, log the anomaly for future verification.

4. Oil Spill Detection Using Hybrid Deep Learning Models

Process the retrieved satellite images using a hybrid model combining UNET and DeepLabV3+.
Each model independently analyzes the image to detect possible oil spills.
If all models confirm the presence of an oil spill, the detection is validated.
If any one model fails to detect a spill, the system does not confirm the spill to prevent false positives.

5. Final Confirmation and Reporting

Confirm oil spill detection if all models agree on the presence of an oil slick.
Correlate the spill with nearby vessel activities using AIS data.
Generate real-time alerts for maritime authorities with spill location, estimated affected area, and suspected vessel involvement.

6.2 IMPLEMENTATION STEPS

The following steps outline the end-to-end implementation of the Oil Spill Detection System, ensuring accurate vessel anomaly detection and oil spill confirmation.

Step 1: AIS Data Collection and Monitoring

Extract AIS vessel movement data (latitude, longitude, SOG, COG, heading, timestamp).

Store the dataset in a structured format using pandas for real-time processing.
Continuously monitor vessel speed and course changes to detect anomalies.

Step 2: Anomaly Detection in Vessel Behavior

Define anomaly conditions based on:

Speed drop greater than 50% within a short period.

Course deviation exceeding 45° unexpectedly.

If anomalies are detected, extract the latitude and longitude coordinates for further analysis.

Step 3: Request Satellite Imagery from Google Earth Engine (GEE)

Query Sentinel-1 and Sentinel-2 for images corresponding to flagged anomaly locations.
If satellite images are available, proceed with deep learning analysis.
If images are not available, log the anomaly for future processing.

Step 4: Image Processing and Oil Spill Detection

Preprocess satellite images by normalizing and enhancing features.
Use a hybrid deep learning model (UNET + DeepLabV3+) to segment oil spill regions.
Each model independently classifies the image for oil spill presence.

Step 5: Oil Spill Confirmation

If all models detect an oil spill, confirm the spill occurrence.
If any model fails to detect the spill, reject the result to prevent false positives.

Step 6: Vessel Correlation and Alert Generation

Identify vessels near detected spill locations using AIS data.
Correlate vessel behavior (speed/course changes) with the detected spill.
Generate real-time alerts with spill details and suspected vessels for maritime authorities.

Step 7: Logging and Continuous Improvement

Store all detected anomalies and model results for future validation and improvement.
Optimize detection accuracy by reducing false positives and retraining models with more data.

6.3 IMPLEMENTATION PROCEDURE

The Oil Spill Detection System follows a structured procedure that begins with continuous monitoring of AIS data, where vessel movements, including speed (SOG) and course (COG), are analyzed for anomalies. If a vessel exhibits a sudden speed drop (more than 50%) or a sharp course deviation (over 45°), it is flagged as suspicious. The system then extracts the latitude and longitude coordinates of the anomaly for further verification.

Once an anomaly is detected, a request is sent to Google Earth Engine (GEE) to retrieve Sentinel-1 and Sentinel-2 satellite images for the specific location and time. If satellite imagery is available, the images undergo preprocessing to enhance visibility and segmentation accuracy. The preprocessed images are then analyzed using a hybrid deep learning model combining UNET and DeepLabV3+, where both models independently segment and classify possible oil spill regions.

To confirm the presence of an oil spill, the system applies a cross-validation approach—if all models detect an oil spill, the detection is confirmed; however, if any one model fails to classify the spill, the system discards the detection to avoid false positives. Once a spill is confirmed, the system correlates vessel movements with detected spill locations using AIS data to identify potential sources.

Following correlation, real-time alerts are generated, providing maritime authorities with spill location details, estimated affected area, and the suspected vessel's MMSI number for further investigation. The system also logs all detected anomalies and spill events, ensuring that data is available for future validation and model refinement. Continuous improvements, including reducing false positives and enhancing scalability, are implemented to ensure real-time monitoring and high detection accuracy.

6.4 USER MANUAL

1.Introduction

The Oil Spill Detection System is designed to monitor vessel anomalies, detect oil spills using satellite imagery, and provide real-time alerts. It integrates AIS vessel movement data with Sentinel-1 and Sentinel-2 satellite images, using a hybrid deep learning approach for accurate spill detection. The system continuously tracks vessel movements, detects anomalies such as sudden speed drops and course deviations, and retrieves satellite images for further analysis. If an oil spill is confirmed using deep learning models, the system generates an alert with relevant spill location and vessel details.

2. System Features

Real-Time Anomaly Detection: Monitors AIS data to identify sudden speed drops and course deviations.

Satellite Image Processing: Fetches Sentinel-1 and Sentinel-2 images from Google Earth Engine (GEE).

Hybrid Deep Learning Model: Uses UNET and DeepLabV3+ for oil spill segmentation.

Vessel Correlation: Links detected spills to nearby vessels based on AIS movement patterns.

Automated Alerts: Generates real-time notifications for confirmed oil spills.

3. System Requirements

Hardware

- Minimum 8GB RAM, 2.5GHz Processor (for local processing).
- NVIDIA GPU (Recommended) for faster deep learning inference.
- Minimum 5th Generation processor

Software

- Python 3.10 (Keras and TensorFlow modules require this version).
- Google Earth Engine API (for retrieving satellite imagery).
- TensorFlow, Keras, OpenCV, pandas, numpy, scikit-learn for deep learning and data processing.

Cloud Services

- Google Earth Engine (GEE): Satellite image retrieval.
- Cloud-based AIS data storage (AWS S3 or Google Cloud Storage, optional).

4. How to Use the System

Step 1: Setup Environment

1. Ensure Python 3.10 and required dependencies are installed
2. Ensure Python 3.10 is installed, You check python version using:

   python --version
3. Install all the required modules and packages which are helpful for the project execution

   pip install numpy pandas matplotlib opencv-python pillow scikit-image

seaborn tensorflow scikit-learn tqdm

4. Authenticate and configure Google Earth Engine (GEE) API:

Step 2: Run Oil Spill Detection System

1. The system automatically loads AIS data from the specified CSV file in the code.
2. Execute the system with:

   python oil_spill_detection.py
3. If an anomaly is detected, the system automatically sends the coordinates to GEE for satellite image retrieval.

5. Output Screen

When the system is executed, it continuously processes AIS vessel data, detects anomalies, retrieves satellite imagery, and runs the deep learning models for oil spill detection. Below is a sample output of the system in action:

```
Processing anomaly at 30.39231, -81.41259 on 2024-01-01
Detected Oil Spill Area (sq. km): 86.6921871443087
1/1 [==============================] - 0s 110ms/step
1/1 [==============================] - 0s 341ms/step
1/1 [==============================] - 0s 366ms/step
No significant oil spills detected across the checked dates.

Processing anomaly at 36.9512, -76.32947 on 2024-01-01
No Sentinel-1 VV or VH images available. Trying Sentinel-2.
No Sentinel-2 images available for this date and location.
```

CHAPTER-7: CONCLUSION AND FUTURE ENHANCEMENTS

7.1 CONCLUSION

This project successfully implemented an automated oil spill detection system by integrating AIS vessel data and satellite imagery (Sentinel-1 and Sentinel-2) with deep learning models (UNET, DeepLabV3+, and a Hybrid Model). The system effectively detected oil spills by analyzing vessel anomalies such as sudden speed drops and course deviations and correlating them with high-resolution satellite images. The hybrid deep learning approach demonstrated superior performance compared to individual models. UNET provided pixel-level accuracy, while DeepLabV3+ enhanced multi-scale segmentation, resulting in improved detection accuracy and reduced false positives. This robust detection capability enhances environmental monitoring and regulatory enforcement, allowing for faster response times in mitigating oil spills.

7.2 FUTURE ENHANCEMENTS

Enhanced Spill Detection Accuracy:

Utilize higher-resolution satellite imagery for better segmentation.

Expand training datasets to improve model performance in diverse conditions.

Real-Time Processing & Alerts:

Implement real-time monitoring for immediate spill detection.

Develop an automated alert system to notify authorities instantly.

Improved AIS Correlation and Vessel Tracking:

Address gaps in AIS data by integrating additional vessel tracking sources.

Optimize anomaly detection algorithms to reduce false positives.

Deployment & Scalability:

Develop a user-friendly interface for environmental agencies.

Implement cloud-based deployment for large-scale monitoring.

These enhancements will further strengthen the system’s accuracy, efficiency, and real-world applicability for maritime pollution monitoring.

Project Mapping with various courses of the Curriculum with attained POs

Name of Course from which Principles are applied in this project	Description of the Application	Attained Pos
C311	Thorough Examination of Existing systems and definition of the problem	PO1,PO2, PO6,PO7
C324, C325, C415	Gathering, Analysis and classification of all the requirements for the proposed system	PO1,PO2,PO4
C425, C314, C225	Logical design is done by using logical tools	PO1, PO2,PO3, PO10
C228, C325, C324	The physical design is done by using Android Studio, and database MySQL.	PO5,PO8,PO10,PO11,PO12
C425, C324, C414	Each and every module is tested, integrated, and evaluated.	PO8,PO10,PO11,PO12
C425, C414	Implementation of the project in the real environment	PO7,PO8,PO10,PO11
C425, C3110, C329	Documentation is done by all the team members with well defined communication with inclusion of Engineering and management Principles	PO8,PO9,PO10,PO11,PO12
C425, C3110, C329	Presentation of the work in teams with proper method of presentation.	PO9,PO8,PO10, PO11

COURSE STRUCTURE (R13)

I YEAR- I SEMESTER

S No	Subject	T	P	Credits
C111	Problem Solving and Programming Using C	3	0	3
C112	Applied Chemistry	3	0	3
C113	Differential Equations	3	0	3
C114	Engineering Graphics	1	4	3
C115	Basics of Electrical and Electronics Engineering	3	0	3
C116	Problem Solving and Programming Using C Lab	0	3	1.5
C117	IT Workshop	0	3	1.5
C118	Applied Chemistry Lab	0	3	1.5
Total Credits				**19.5**

I YEAR- II SEMESTER

S No	Subject	T	P	Credits
C121	Communicative English	3	0	3
C122	Applied Physics	3	0	3
C123	Linear Algebra & Vector Calculus	3	0	3
C124	Digital Logic Design	3	0	3
C125	Python Programming	3	0	3
C126	Environmental Sciences	2	0	0
C127	Communicative English Skills Lab	0	3	1.5
C128	Applied Physics Lab	0	3	1.5
C129	Python Programming Lab	0	3	1.5
Total Credits				**19.5**

II YEAR- I SEMESTER

S No	Subject	T	P	Credits
C211	Probability & Statistics	3	0	3
C212	Mathematical Foundations of Computer Science	3	0	3
C213	Data Structures & Algorithms	3	0	3
C214	Object Oriented Programming through Java	3	0	3
C215	Introduction to Artificial Intelligence	3	0	3
C216	Constitution of India	2	0	0
C217	Data Structures &Algorithms Lab	0	3	1.5
C218	Object Oriented Programming through Java lab	0	3	1.5
C219	Introduction to Artificial Intelligence Lab	0	3	1.5
C2120	Skill Oriented Course -1	1	2	2.0
Total Credits				**21.5**

II YEAR- II SEMESTER

S No	Subject	T	P	Credits
C221	Numerical Methods & Transformations	3	0	0
C222	Computer Organization	3	0	0
C223	Database Management Systems	3	0	0
C224	Formal Languages and Automata Theory	3	0	0
C225	Managerial Economics and Financial Accountancy	3	0	0
C226	Database Management Systems Lab	0	0	3
C227	Web Application Development Lab	0	0	3
C228	R Programming Lab	0	0	3
C229	Skill Oriented Course -2	1	0	2
Total Credits				**21.5**

III YEAR- I SEMESTER

S No	Subject	T	P	Credits
C311	Design and Analysis of Algorithms	3	0	3
C312	Machine Learning	3	0	3
C313	Operating Systems	3	0	3
C314	Professional Elective -1	3	0	0
C315	**Open Elective -1**	3	0	3
C316	**Skill Oriented Course – III**	0	4	2
C317	Professional Ethics and Human Values	2	0	0
C318	**Summer Internship one Month (Mandatory) after second year(to be evaluated during V Semester**	0	0	1.5
C319	Machine Learning Lab	0	3	1.5
C3110	Operating Systems Lab	0	3	1.5
Total Credits				**21.5**

III YEAR- II SEMESTER

S No	Subject	T	P	Credits
C321	Computer Networks and communications	3	0	3
C322	Deep Learning	3	0	3
C323	Expert Systems	3	0	3
C324	**Professional Elective -2**	3	0	3
C325	**Open Elective -2**	3	3	3
C326	**Skill Oriented Course – IV (Soft Skills)**	0	2	2
C327	Intellectual property rights and patents (IPR&P)	2	0	0
C328	Deep Learning Lab	0	3	1.5
C329	Computer Networks and communications Lab	0	3	1.5
C3210	Mini Project with seminar	1	2	1.5
Total Credits				**21.5**

IV YEAR- I SEMESTER

S No	Subject	T	P	Credits
C411	**Professional Elective-III**	3	0	3
C412	**Professional Elective-IV**	3	0	3
C413	**Professional Elective-V**	3	0	3
C414	**Open Elective-III**	3	0	3
C415	**Open Elective - IV**	3	0	3
C416	Management Science	3	0	3
C417	**Skill Oriented Course** –V	0	4	2
C418	**Industrial/Research Internship one months (Mandatory) after third year (to be evaluated during VII semester)**	0	0	1.5
Total Credits				**23**

IV YEAR- II SEMESTER

S No	Subject	T	P	Credits
C421	Project work - Phase II	0	0	12
Total Credits				**12**

OPEN ELECTIVES		
Open Elective – 1 (V Semester) Python Programming	Open Elective -2 (VI Semester) Fundamentals of Artificial Intelligence	Open Elective -3 (VII Semester) Human Computer Interaction
Open Elective -4 (VII Semester) Applications of Artificial Intelligence	Skill Oriented Course (Advanced)– IV 1. (MEAN Stack Technologies - Module I- MongoDB, Express.js, Angular JS, Node.js and AJAX 2. Big Data : Apache Spark 3. DevOPS	
PROFESSIONAL ELECTIVES		
Professional Elective – 1 (V Semester)	**Professional Elective – 2** **(VI Semester)**	**Professional Elective – 3** **(VII Semester)**
1. Software Engineering 2. Compile Design 3. Data Visualization 4. Design and Analysis of Algorithms	1. Software Project Management 2. Distributed Systems 3. Internet of Things 4. Data Where Housing and Data Mining	1.Reinforcement Learning 2.Soft Computing 3. Cryptography and Network Security 4. NOSQL Databases 5. Natural Language Processing
Professional Elective – 4 (VII Semester)	Professional Elective – 5 (VII Semester)	
1. Robotic Process Automation 2. Cloud Computing 3. Big Data Analytics 4. Block Chain Technologies 5. Image & Video Analytics	1. Social Network Analysis 2. Recommender Systems 3. Computer vision 4. Object Oriented Analysis and Design 5. Semantic Web	

CHAPTER-8: BIBLIOGRAPHY

A bibliography is a list of sources, such as books, articles, or websites, that have been used in the research or creation of a particular work, such as a research paper, book, or presentation. The purpose of a bibliography is to give credit to the sources that have been consulted and to enable readers to locate and verify the information used in the work. A bibliography typically includes the author's name, the title of the work, the date of publication, the publisher, and any other relevant information that will help readers locate the source. There are different citation styles for creating a bibliography, such as APA, MLA, Chicago, and Harvard, which provide guidelines for formatting the citations.

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[18] Lee, D. J., et al. "Integration of Deep Learning and AIS for Maritime Surveillance," IEEE Transactions, VOLUME 8, 2020, Page No: 60123-60134, Digital Object Identifier: 10.1109/ACCESS.2020.3067123

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[20] Kumar, N., et al. "Deep Feature Extraction for Oil Spill Image Recognition," IEEE Transactions, VOLUME 7, 2019, Page No: 38899-38912, Digital Object Identifier: 10.1109/ACCESS.2019.2849932

8.2 Books Referred and Websites Visited

BOOKS:

1. Jensen, J. R.

"Remote Sensing of the Environment: An Earth Resource Perspective."

Publisher: Pearson Prentice Hall, 2005

Covers the fundamentals of remote sensing technologies, including satellite-based oil spill detection techniques.

2. Buyya, Rajkumar, Broberg, James, & Goscinski, Andrzej

"Cloud Computing: Principles and Paradigms."

Publisher: Wiley, 2011

Discusses data processing techniques in cloud-based environments, relevant for handling large-scale AIS and satellite data.

3. Pattiaratchi, C., et al.

"Modelling the Transport and Fate of Oil Spills Using Hydrodynamic Models."

Publisher: Elsevier, 2016

Explores ocean current modeling and oil spill movement predictions, essential for tracking detected spills over time.

JOURNALS:

4. Chassignet, E. P., et al.

"Oil Spill Monitoring Using Satellite SAR Imagery and AIS Data."

Journal: Journal of Marine Systems, Vol. 81(3), 2010

Examines how Synthetic Aperture Radar (SAR) and AIS data can be integrated for oil spill detection.

5. Zhang, L., et al.

"Deep Learning-Based Detection of Oil Spills Using Satellite Imagery."

Journal: Remote Sensing, Vol. 11(9), 2019

Proposes a deep learning approach for segmenting oil spills in Sentinel-1 and Sentinel-

2 images.

6. Mei, F., et al.

"Application of Machine Learning Techniques in Oil Spill Detection and Response: A Comprehensive Review."

Journal: Journal of Environmental Management, Vol. 231, 2019

Reviews various machine learning-based models used for oil spill detection and classification.

7. Huang, C., et al.

"Satellite-Based Remote Sensing for Oil Spill Detection and Monitoring: A Review."

Journal: Environmental Science and Pollution Research, Vol. 26(9), 2019

Analyzes the effectiveness of remote sensing technologies in identifying oil spills from marine environments.

8.2 WEBSITES VISITED:

Kaggle - (https://www.kaggle.com/datasets/nabilsherif/oil-spill):

Provides Sentinel-1 SAR imagery annotated for oil spills, essential for training deep learning models like U-Net and DeepLabV3.

The dataset includes training and testing directories, enabling the development of a robust oil spill detection system.

Marine Cadastre - AIS Vessel Data (https://marinecadastre.gov/accessais/):

Offers Automatic Identification System (AIS) data, which helps track vessel movements and detect anomalies related to potential oil spills.

AIS data is critical for identifying ships near detected spills, aiding in spill source attribution and regulatory enforcement.

Google Earth Engine (GEE) (https://earthengine.google.com/):

A cloud-based platform providing access to Sentinel-1 and Sentinel-2 satellite imagery, crucial for real-time oil spill detection.

Enables geospatial analysis, satellite image processing, and deep learning integration, allowing efficient large-scale monitoring.

CONFERENCE CERTIFICATES


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for presenting a Research Paper titled

REAL-TIME OIL SPILL DETECTION USING AIS AND SATELLITE DATA INTEGRATION

with Paper ID 17 in National Conference on Innovative Challenges in Deep Learning and its Applications -NCICDLA-25 held during 28th and 29th of March-2025.

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Principal

Dr. K. Hari Babu
Director

Dr. G. Murali
Conference-Chair

Dr. S. Radhakrishnan
Conference-Convener

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Dr. P. Babu	Dr. K. Hari Babu	Dr. G. Murali	Dr. S. Radhakrishnan
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INTERNSHIP CERTIFICATES

CERTIFICATE

OF COMPLETION

This certificate is proudly presented to:

UDAY AMBATI

This is to certify that UDAY KIRAN AMBATI has successfully completed an internship in Web Development & AI Tools. The internship period was from 1st December 2024 to 1st April 2025, during which the candidate demonstrated exceptional skills and contributed to various projects.

Yuhui Radha
Human Resource Manager

Venu Babu
Program Coordinator

ANDHRA PRADESH STATE COUNCIL OF HIGHER EDUCATION

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Certificate of Completion

Certificate Id: **BBAPSCHDE2025LTIN000113**

This is to certify that **NARENDRANATH ATHOTA**, bearing Reg. No: **21JR1A4340**, from **KKR & KSR Institute Of Technology And Sciences, Vinjanampadu**, has successfully completed a **Long-term internship** for **240 hours** on **Business Analytics** in the year **2025.** This internship was organized by **Blackbuck Engineers**, in association with the **Andhra Pradesh State Council of Higher Education (APSCHE).**

Anuradha Thota
Chief Executive Officer
Blackbuck Engineers Pvt. Ltd.

Date: 17/03/2025
Place: Hyderabad

APSCHE

BLACKBUCK ENGINEERS

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Certificate of Completion

Certificate Id: **BBAPSCHDE2025LTIN0011459**

This is to certify that **CHILUKA RAJESH BABU,** bearing Reg. No: **21JR1A4356**, from **KKR & KSR Institute Of Technology And Sciences, Vinjanampadu**, has successfully completed a **Long-term internship** for **240 hours** on **Businees Analytics** in the year **2025**. This internship was organized by **Blackbuck Engineers**, in association with the **Andhra Pradesh State Council of Higher Education (APSCHE).**

BLACKBUCK ENGINEERS PVT. LTD. HYDERABAD

Anuradha Thota
Chief Executive Officer
Blackbuck Engineers Pvt. Ltd.

Date: 17/03/2025
Place: Hyderabad

CERTIFICATE
OF COMPLETION

This Certificate is Awarded to

Nagasai Gangineni

This is to certify that **Nagasai Gangineni**, has successfully completed an internship with **Swift Stratagic Solution from [Dec, 2024] to [April, 2025].**
During this period, **Nagasai Gangineni** worked in the Hr - Executive and payroll Assistence and was involved in various tasks and responsibilities
We wish them the best of luck in their academic and professional career.

Somajiguda, Hyderabad,
April 1st, 2024

Murad Naser
CEO

Pandit
HR Director

BLACKBUCK ENGINEERS

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Certificate Id: **BBAPSCHDE2025LTIN000959**

This is to certify that **Chikkala Ramesh ,**bearing Reg. No: **21JR1A4354**, from **KKR & KSR Institute Of Technology And Sciences, Vinjanampadu** , has successfully completed a **Long-term internship** for **240 hours** on **Full Stack Development** in the year**2025.** This internship was organized by **Blackbuck Engineers**, in association with the **Andhra Pradesh State Council of Higher Education (APSCHE).**

Anuradha

BLACKBUCK ENGINEERS PVT. LTD. HYDERABAD

Anuradha Thota
Chief Executive Officer
Blackbuck Engineers Pvt. Ltd.

Date: 17/03/2025
Place: Hyderabad