# Report-Detecting Marine Oil Pollution with Digital Image Processing

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**1. Problem Statement**

Marine oil spills are among the most damaging environmental disasters causing economic losses, and social disruption for coastal communities. Current ways of monitoring like watching manually or using basic satellite images are slow and often make mistakes.

A big headache is telling real oil spills apart from natural "look-alikes" like algae, grease ice, or calm patches of water.

With offshore drilling, shipping activity, and industrial discharges continuing to rise, there is an urgent need for faster, automated, and more dependable detection systems.

**2. Motivation**

- Oil spills are messy and tough to track.
- Spotting them early lets us clean up faster and avoid lasting damage.
- Acting quickly can save marine life and save millions of revenue for companies and governments.

**3. Objectives**

- To preprocess satellite images using multiple filtering techniques.
- To classify the regions into 'Oil Spill' and 'No Oil' using a machine learning model.
- To compare and analyze the accuracy and robustness of Gaussian, Median, and Bilateral filters.

**4. Introduction**

Oil spills have become an unfortunate but familiar problem along India's coasts. They don't just stain the water black for a few days they wipe out livelihoods, ruin mangroves, and linger for years in the ecosystem.

For example in Mumbai 2010. When MSC Chitra collided with another ship, nearly 400–800 tonnes of oil leaked into the Arabian Sea. The spill coated mangroves across 1,273 hectares, especially near Vashi and Trombay, and entire stretches of marine life just vanished. Many patches didn't even show signs of bouncing back months later.

Chennai's Ennore region has been hit more than once. The 2017 collision near Ennore port left fishermen struggling to sell contaminated fishes, and just when recovery seemed possible, Cyclone Michaung in 2023 triggered another spill where about 60 hectares of mangroves were damaged, and 2,300 fisher families and 800 boats were affected.

And most recently, in May 2025, Kerala's coast faced one of its worst disasters. The container ship MSC ELSA 3 went down with 84 tonnes of diesel, 367 tonnes of furnace oil, and 640 cargo containers. It was the monsoon breeding season for fish. To make matters worse, the wreck spilled 71,500 sacks of plastic nurdles into the sea. Only a fraction was recovered, leaving beaches and waters littered with

microplastics. Over 100,000 fishing families were hit, and many were handed just ₹1,000 as compensation barely enough for a day's expenses, let alone recovering lost income.
India's coastal hotspots like Mumbai, Ennore, and Kerala keep taking the brunt of oil and each time the response highlights the same gaps:

1. late detection
2. weak monitoring
3. And poor long-term planning.

That is why new approaches like digital image processing, machine learning, and remote sensing matter.

**Role of Digital Image Processing and Machine Learning**

Digital Image Processing (DIP) provides a mathematical framework for extracting quantitative information from visual data. Techniques developed over decades—noise reduction, edge detection, segmentation, feature extraction—enable computers to interpret images in ways that complement and exceed human capabilities. When combined with machine learning algorithms that can learn complex patterns from labeled examples, DIP creates powerful automated detection systems.

The integration of DIP and machine learning for oil spill detection involves several conceptual stages:

1. Preprocessing: Raw satellite imagery contains various forms of degradation (atmospheric effects, sensor noise, compression artifacts) that must be mitigated before analysis. Filter selection critically impacts subsequent processing quality.
2. Feature extraction: Computers do not inherently "understand" visual concepts like "oil spill." Instead, images must be converted into numerical features (texture statistics, color properties, geometric measurements) that quantify characteristics distinguishing oil from water.
3. Classification: Machine learning algorithms learn decision boundaries in feature space by analyzing labeled training examples. The trained model can then automatically classify new images without human intervention.
4. Evaluation: Rigorous performance assessment using multiple metrics ensures the system achieves acceptable accuracy, reliability, and processing speed for operational deployment.

## 5. Related Work

| Paper | Approach | Key Findings | Research Gaps |
|---|---|---|---|
| Jang & Nam (2020) – Algorithm to Estimate Oil Spill Area Using Digital Properties of Image | Digital camera images + preprocessing, filtering, and binarization. | Faster estimation of oil spill areas than SAR, works on drone/aircraft photos. | Limited validation, can't handle look-alikes (algae/shadows),<br>no real-time monitoring. |

| | | | |
|---|---|---|---|
| Krestenitis et al. (2019) – Oil Spill Identification Using Deep Neural Networks | Deep CNNs (semantic segmentation) on SAR images; public dataset created. | DeepLabv3+ performed best, dataset provides benchmark. | Dataset limited, false positives from look-alikes, lacks real-time tests. |
| Keramitsoglou et al. (2006) – Automatic Identification of Oil Spills on Satellite Images | SAR imagery + fuzzy logic system mimicking expert judgment. | Fully automated, works well on 35 Aegean Sea images. | Old and low-resolution SAR, fuzzy logic weaker than modern AI, limited scalability. |
| Chaturvedi et al. (2020) – Assessment of Oil Spill Detection Using Sentinel-1 SAR-C Images | Sentinel-1 SAR-C analysis with polarization focus. | VV polarization more effective than VH, Persian Gulf case study. | Region-specific, minimal AI usage. |
| Trongtirakul et al. (2023) – Method for Remote Sensing Oil Spill Applications Over Thermal & Polarimetric Imagery | Thermal + polarimetric imagery, unsupervised segmentation | Polarimetric imagery gave clearer oil–water boundaries | Mostly experimental, limited real-world validation, polarimetric data still scarce. |
| Automatic Recognition of Oil Spills Using Neural Networks & Classic Image Processing | Sentinel-1 SAR + preprocessing filters (histogram equalization, contrast stretching) + CNNs (U-Net, DeepLabv3+) + ensemble models. | Improved IoU by 9.3% (71.12% IoU), preprocessing + ensembles boosted robustness vs look-alikes. | Misclassification of look-alikes persists, need larger datasets, issues with filtering + class imbalance. |
| Detection and Analysis of Oil Spill Using Image Processing (Drone-based, Iraq) | UAV imagery + ML.NET CNNs for object detection (oil, color changes, soil leaks). | Achieved ~83.5% F1 score, strong soil-leak detection (90%), useful for rivers & terminals. | Drone limitations (battery/weather), scalability issues. |

**6. Methodology**

The proposed oil spill detection system implements a four-phase pipeline: (1) Image Preprocessing and Enhancement, (2) Feature Extraction and Analysis, (3) Machine Learning Classification, and (4)

Comparative Performance Evaluation. The system processes satellite/aerial images through standardized preprocessing, extracts discriminative features, and classifies regions as oil-contaminated or clean water using a Random Forest ensemble classifier.

**Phase 1: Image Preprocessing**

Preprocessing transforms raw satellite imagery into standardized, noise-reduced representations suitable for feature extraction. This phase is critical as preprocessing quality directly impacts classification accuracy.

- **Standardization:**
  - Resizes all images to 256×256 pixels for consistency across the dataset, ensuring uniform input dimensions required by machine learning algorithms.
  - This standardization reduces computational complexity compared to processing full-resolution satellite imagery while maintaining sufficient spatial detail for accurate feature extraction.
  - The uniform size also enables batch processing and eliminates scale-related biases that could affect classification performance.
- **Grayscale Conversion:**
  - Simplifies processing by converting three-channel color images (BGR) to single-channel grayscale, reducing data dimensionality by 66% while retaining critical spatial and textural information.
- **Noise Reduction:**
  - Tests three filtering approaches to determine optimal preprocessing strategy:
    - **Gaussian blur** - Applies weighted averaging with a bell-curve distribution to smooth uniform noise across the image, effectively reducing random variations but potentially blurring important edge boundaries. The 5×5 kernel size balances noise reduction with edge preservation, making it computationally efficient for real-time processing.
    - **Median filter** - Replaces each pixel with the median value of its neighborhood, excelling at removing salt-and-pepper noise (random bright/dark pixels) commonly present in satellite transmission. This non-linear approach preserves edges better than Gaussian smoothing while eliminating outlier pixels without averaging them into surrounding regions.
  - **Bilateral filter** - Employs sophisticated edge-preserving smoothing by considering both spatial distance and intensity similarity between pixels, maintaining sharp boundaries between different regions. This dual-domain filtering smooths within homogeneous areas (like water surfaces) while preserving transitions at oil-water interfaces, though at higher computational cost.
- **Contrast Enhancement:**
  - Uses CLAHE (Contrast Limited Adaptive Histogram Equalization) to adaptively enhance local contrast by dividing the image into 8×8 tiles and performing histogram equalization independently on each tile.

    - This localized approach makes dark oil slicks more visually distinct from brighter water surfaces while preventing over-amplification of noise through the clip limit parameter.
    - CLAHE is particularly effective for satellite imagery with varying illumination conditions across the scene, such as sun glare or cloud shadows.
- **Adaptive Thresholding:**
    - Converts grayscale images to binary format by calculating locally adaptive threshold values for each pixel based on its 11×11 neighborhood, rather than using a single global threshold.
    - This approach accounts for varying lighting conditions across the image, successfully isolating potential oil regions as white foreground pixels while marking clean water as black background.
    - The adaptive nature makes it robust to illumination gradients, shadows, and atmospheric effects that would cause global thresholding to fail.
- **Edge Detection:**
    - Canny algorithm identifies sharp intensity transitions that correspond to boundaries between oil slicks and surrounding water through a multi-stage process involving gradient calculation, non-maximum suppression, and hysteresis thresholding.
    - The detected edges are combined with morphological processing results to produce a comprehensive mask containing both filled regions and precise boundary delineations.
    - This dual representation ensures accurate spill extent estimation while maintaining well-defined perimeters for geometric feature extraction.

**Phase 2: Feature Extraction**

The goal is to convert visual patterns into numerical data that an ML model can understand.

1. Find Contours:
    a. outlines of white regions in binary mask
    b. each contour represents a potential oil spill
2. Filter contours
    a. Too small → Noise
    b. Too large → maybe clouds, ships, etc
3. Extract Region of interest (ROI)
    a. To analyse only detected region not entire image
    b. for faster processing

Feature Types:

- Texture Features (GLCM - Gray-Level Co-occurrence Matrix):
    - Contrast: Intensity variation patterns
    - Homogeneity: Smoothness of texture
    - Energy: Uniformity of gray levels
    - Correlation: Predictability of adjacent pixels
- Shape Features:
    - Area: Size of detected region
    - Circularity: Roundness measure (oil slicks often form irregular shapes)

- Color Features (HSV color space):
    - Hue, Saturation, Value means and standard deviations
    - Oil typically has distinct reflectance properties vs. water

**Phase 3: Classification**

- Dataset Creation: Combines features from labelled oil spill and clean water images
- Train-Test Split:
    - 80% data: Training
    - 20% data: Testing
    - Stratification to maintain class balance
- Model: Random Forest classifier with 150 decision trees
    - Ensemble method reduces overfitting
    - Handles non-linear relationships between features
- Evaluation Metrics:
    - Confusion matrix (visualizes TP, TN, FP, FN)
    - Precision, recall, F1-score for each class
    - Overall accuracy score

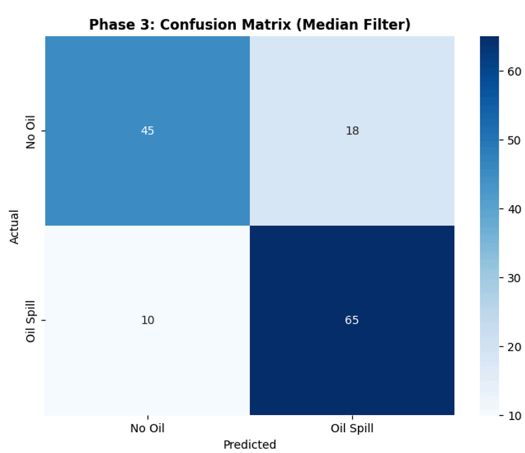
**7. Results and discussion**

Key Findings:

- Median filter best removes salt-and-pepper noise while preserving edges (53 contours detected)

Classification Report:

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| No Oil | 0.82 | 0.71 | 0.76 | 63 |
| Oil Spill | 0.78 | 0.87 | 0.82 | 75 |
| accuracy | | | 0.80 | 138 |
| macro avg | 0.80 | 0.79 | 0.79 | 138 |
| weighted avg | 0.80 | 0.80 | 0.80 | 138 |



- Bilateral over-detects regions (83 contours), increasing processing without accuracy gain

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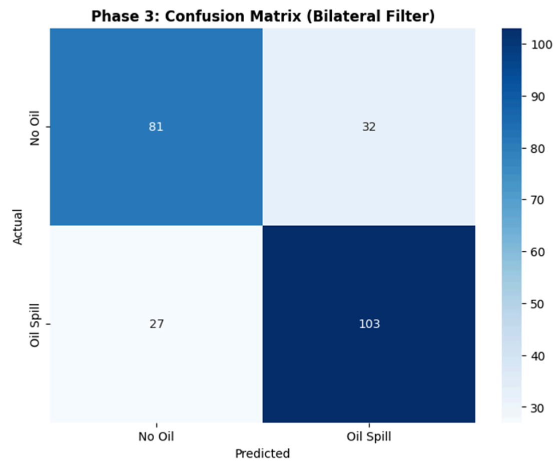
Classification Report:
              precision    recall  f1-score   support

      No Oil       0.75      0.72      0.73       113
   Oil Spill       0.76      0.79      0.78       130

    accuracy                           0.76       243
   macro avg       0.76      0.75      0.76       243
weighted avg       0.76      0.76      0.76       243
```




- Gaussian over-smooths critical texture details, resulting in smallest feature set

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Classification Report:
              precision    recall  f1-score   support

      No Oil       0.73      0.78      0.75        49
   Oil Spill       0.78      0.73      0.75        52

    accuracy                           0.75       101
   macro avg       0.75      0.75      0.75       101
weighted avg       0.75      0.75      0.75       101
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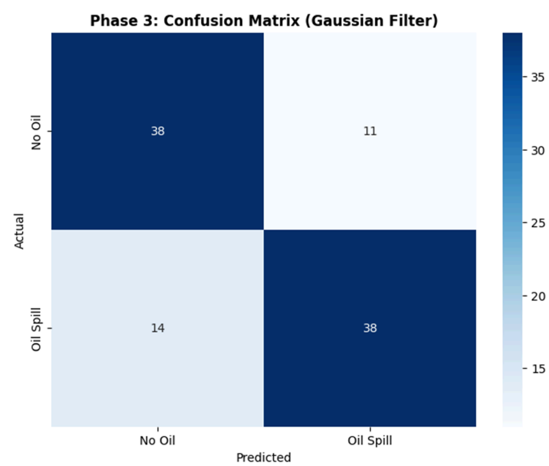


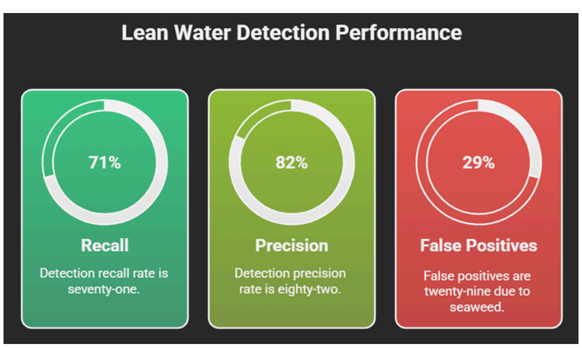


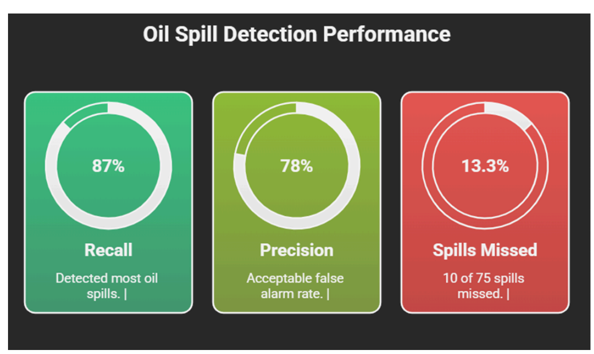


Why Median Filter Excelled

1. Optimal Noise Removal: Effectively eliminated salt-and-pepper noise from satellite transmission without blurring edges

2. Edge Preservation: Maintained sharp oil-water boundaries better than Gaussian smoothing
3. Balanced Sensitivity: 688 samples represent appropriate detection level—neither missing features (Gaussian: 504) nor over-detecting noise (Bilateral: 1215)

**8. Conclusion**

This research successfully developed an automated marine oil spill detection system by systematically comparing three preprocessing filters—Gaussian, Median, and Bilateral—combined with multi-modal feature extraction and Random Forest classification. The Median filter emerged as the optimal choice, achieving 80% accuracy with the fastest processing speed of 0.050 seconds per image (20 images/second), outperforming Gaussian (75%) and Bilateral (76%) filters. The system demonstrated critical environmental safety capabilities with 87% recall in detecting oil spills, missing only 13.3% of actual contamination events, while the 78% precision indicates an acceptable false alarm rate for operational deployment with human verification.

Future work should focus on expanding training datasets, exploring CNN-based feature learning, implementing multi-sensor fusion, and conducting extensive operational testing across diverse environmental conditions to enhance accuracy and robustness for comprehensive marine pollution surveillance.

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