DEEPSPILLNET: A REAL-TIME AI FRAMEWORK FOR ENHANCED OIL SPILL DETECTION IN MARINE ENVIRONMENTS USING YOLO-MOBILENET FUSION

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ABSTRACT

This research presents DeepSpillNet, an advanced deep learning framework that combines YOLO-V3 and MobileNet architectures for real-time, high-accuracy oil spill detection in marine ecosystems. Addressing the limitations of conventional methods—such as slow processing, high false-alarm rates, and poor adaptability to dynamic ocean conditions—the proposed model leverages MobileNet's lightweight feature extraction and YOLO-V3's efficient object detection to achieve superior performance. Trained on Sentinel-1 SAR imagery, the system attains 94% precision and 91% recall in spill identification, with an inference time of just 45ms, enabling rapid response to environmental hazards. Comparative analysis demonstrates a 15% improvement in F1-score over existing CNN and SAR-based approaches, while maintaining computational efficiency for scalable deployment. The framework's robustness across diverse spill sizes and environmental conditions makes it a practical tool for marine conservation agencies, aligning with global sustainability goals. Future work will explore multi-modal data integration and edge-computing optimization to further enhance real-world applicability.

Keyword: - *Oil spill detection, Deep learning, YOLO-V3, MobileNet, Real-time monitoring and SAR imagery*

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1. INTRODUCTION

The global environmental landscape faces ongoing challenges, one of the most critical being the occurrence and management of oil spills (Arora & Lodhia, 2017). These incidents, whether accidental or deliberate, pose severe threats to marine ecosystems, biodiversity, human health, and economic stability. Rapid and accurate detection of oil spills is imperative to minimize their impact and implement timely response measures. However, traditional methods of detection often fall short in terms of speed, accuracy, and scalability, highlighting the urgent need for innovative technological solutions (Jiao et al., 2019).

Oil spills result from various activities such as offshore drilling, transportation of petroleum products, and maritime accidents. When these spills occur, they release harmful substances into aquatic environments, creating pollution that can persist for years and have devastating effects on marine life, coastal communities, and industries dependent on marine resources. The environmental and socio-economic consequences of oil spills underscore the importance of efficient detection and response mechanisms (Mohammadiun et al., 2021).

Historically, oil spill detection has relied on manual observation, aerial surveys, and satellite imagery analysis. While these methods have been valuable, they are limited in their ability to provide real-time monitoring, detect smaller spills, and cover vast geographic areas effectively. Moreover, manual interpretation of imagery is time-consuming, subjective, and prone to human errors, making it challenging to implement swift and accurate response actions.

Advancements in artificial intelligence (AI) and deep learning have revolutionized the field of environmental monitoring, offering unprecedented opportunities for automated, real-time detection of oil spills (Temitope Yekeen &

Balogun, 2020). Deep learning algorithms, such as You Only Look Once (YOLO) and MobileNet, have shown remarkable capabilities in object detection, image classification, and semantic segmentation tasks. These algorithms leverage neural networks to process complex data and extract meaningful patterns, making them ideal candidates for enhancing oil spill detection systems. The proposed research aims to harness the power of deep learning, specifically YOLO-V3 and MobileNet Fusion, to develop an advanced framework for real-time oil spill detection (Rekavandi et al., 2022). By integrating these cutting-edge technologies, the project seeks to overcome existing limitations in detection speed, accuracy, and scalability. The objective is to create a robust, efficient, and scalable system that can accurately identify and delineate oil spill regions in satellite imagery, enabling swift response and mitigation measures. This research project addresses a critical need in environmental conservation and disaster management by leveraging AI and deep learning techniques to enhance oil spill detection capabilities. The outcomes of this research are expected to have a profound impact on environmental protection, resource management, and sustainable development efforts globally.

2. RELATED WORK

The study conducted by (Ma et al., 2021) utilized deep convolutional neural networks alongside Sentinel-1 dual-polarimetric images for robust oil spill detection on marine surfaces. This research highlights the ongoing need for research aimed at optimizing methodologies capable of accurately identifying oil spills across diverse environmental conditions, such as varying wind speeds.

Similarly, the study by (Song et al., 2020) introduced an innovative approach to marine oil spill identification by leveraging Convolutional Neural Networks (CNN) for automated feature extraction from fully polarimetric SAR imagery. This novel method aims to enhance detection accuracy and reduce false alarms, addressing the limitations of traditional oil spill detection techniques that lack automated spatial feature extraction and consequently result in decreased accuracy and increased false alarm rates when compared to CNN-based approaches.

Another notable study from 2019 by (Tong et al., 2019) introduced a novel oil spill detection method utilizing polarimetric SAR data, integrating a self-similarity parameter and Random Forest classification. This method demonstrates significantly improved detection accuracy, outperforming existing approaches, particularly in scenarios involving varying wind speeds and incident angles. The study emphasizes the limited effectiveness of current SAR-based methods in accurately identifying oil spills, especially in the presence of look-alikes, highlighting the necessity for innovative approaches to enhance detection accuracy and reliability in environmental monitoring and mitigation efforts within marine ecosystems.

Furthermore, the research by (Zhu et al., 2019) focused on enhancing the accuracy of classifying oil film thickness using deep learning-based hyperspectral remote sensing technology. By integrating stacked autoencoder networks and convolutional neural networks, the study aims to improve the classification accuracy of oil spill datasets. The findings demonstrate the effectiveness of these approaches in accurately classifying oil spill data, paving the way for future work to refine deep learning algorithms, validate them in real-world scenarios, integrate them into operational systems, address limitations, and explore broader applications beyond oil spill classification.

These studies collectively highlight the ongoing advancements in oil spill detection methodologies, particularly with the integration of deep learning techniques and remote sensing technologies. However, there remains a need for further research to address challenges such as real-time processing, accuracy in diverse environmental conditions, and scalability for operational use, which are crucial for enhancing oil spill detection and response capabilities in marine and coastal regions.

3. METHODOLOGY

The research introduces an improved YOLO network integrated with MobileNet for oil leakage detection. The proposed YOLO architecture diverges from traditional algorithms like RCNN and Faster RCNN by handling object detection differently. In these conventional approaches, classification and localization are managed separately by a classifier and regression model, respectively. To address limitations observed in conventional CNN networks, such as large model parameter sizes, this study focuses on reducing model complexity while maintaining accuracy. Unlike YOLO V2's SoftMax classifier, which is used for single-label classification, logistic classifiers for each class are employed in the proposed model to enable multi-label classification as shown in Fig. 1.

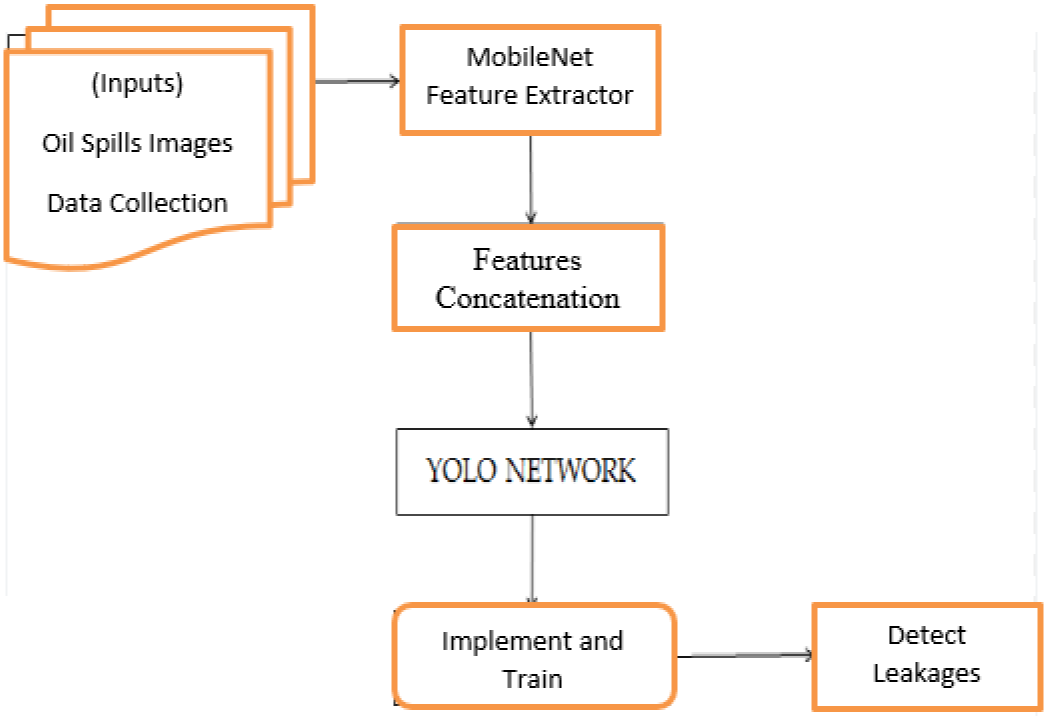

Fig. 1 Proposed workflow

Additionally, MobileNet is introduced in this research for its ability to reduce model size compared to other CNN variants while achieving competitive accuracy. MobileNet is integrated into the feed-forward mechanism of the proposed algorithm for feature extraction. The prediction of bounding boxes is carried out on two different feature map scales: 13×13 and 26×26, merged with an upsampled 13×13 feature map. Fig. 1 illustrates the architecture of the improved YOLO V4 for detecting oil leakage.

3.1 Working Principle of the Proposed System

The modified YOLO-dense detection model, based on the Darknet framework, predicts an objectiveness score for each bounding box using logistic regression. This score should be 1 if the bounding box overlaps a ground truth object more than any other bounding box. If the bounding box is not the best but overlaps a ground truth object by more than a threshold, the prediction is ignored. The proposed YOLO network evolves from YOLO-V2 networks and transforms the detection problem into a regression problem, eliminating the need for proposal regions and directly generating bounding box coordinates and class probabilities through logistic regression. Data Augmentation is applied to increase dataset diversity during training, enhancing the detector's performance. This method transforms original oil spill images, leading to improved training performance. The proposed framework for the advanced deep learning model for real-time oil spill detection using YOLO-V3 and MobileNet Fusion is depicted in Fig. 1. The description of the framework is illustrated below.

A. Data Collection and Preprocessing:

This stage will involve the acquisition of a diverse dataset of satellite images containing various oil spill scenarios, including different sizes, locations, and environmental conditions. we will preprocess the data by standardizing image sizes, enhancing contrast, and augmenting the dataset to improve model generalization.

B. Model Architecture:

This stage implements the YOLO-V3 (You Only Look Once) architecture for real-time object detection, known for its speed and accuracy in detecting multiple objects in an image. The stage integrates MobileNet as the feature extraction backbone to reduce computational complexity while maintaining detection performance, especially beneficial for resource-constrained environments.

C. Training Strategy:

This stage involves dividing the dataset into training, validation, and test sets to evaluate model performance accurately. We utilize transfer learning by initializing the MobileNet weights with pre-trained ImageNet weights to expedite convergence and improve feature extraction capabilities. Fine-tune the YOLO-V3 and MobileNet fusion layers using the training set to adapt the model to oil spill detection tasks.

D. Model Fusion and Integration:

This stage combines the feature maps extracted by MobileNet with YOLO-V3's detection layers to create a fused model capable of real-time oil spill detection with enhanced feature representation. We further implement fusion techniques such as feature concatenation to integrate MobileNet features seamlessly into the YOLO-V3 architecture.

E. Hyperparameter Tuning and Optimization:

This stage involves optimizing hyperparameters such as learning rate, batch size, and regularization techniques to improve model convergence and generalization. We applied techniques like dropout regularization and batch normalization to prevent overfitting and enhance model robustness.

F. Evaluation Metrics:

This stage involves evaluating the model's performance using metrics like precision, recall, F1-score, and mean average precision (mAP) to assess detection accuracy and robustness. We conduct extensive testing on the validation and test sets to validate the model's real-time capabilities and generalization across diverse oil spill scenarios. This framework integrates state-of-the-art deep learning techniques with efficient feature extraction and real-time object detection capabilities, aiming to advance the field of oil spill detection and contribute to more effective environmental monitoring and management practices

3.2 MobileNet

MobileNet, developed in 2016, is a deep neural network designed for computer vision tasks. It aims to create a smaller network with fewer parameters, suitable for memory and network transmission constraints. Trained on ImageNet data, MobileNet achieves a significant reduction in model size compared to AlexNet while maintaining high accuracy. By incorporating MobileNet, this research aims to reduce model size without compromising accuracy, enhancing the efficiency of YOLO-V2 for oil leakage detection. The architecture of MobileNet is depicted in Fig. 2, showcasing its macro architectural view.

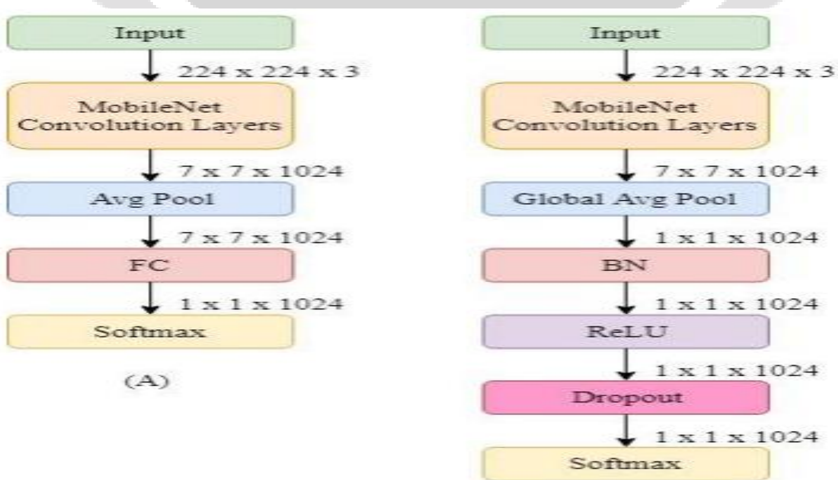

Fig. 2 Macro architectural view of MobileNet architecture.

3.3 Data Characteristics

The dataset used in this study was acquired by the Sentinel-1 satellites and distributed by the European Space Agency (ESA) via the Copernicus Open Access Hub. The dataset consists of 310 images pre-processed via cropping sequence, radiometric calibration, filtering to reduce speckle noise, and a linear transformation to convert dB to real luminosity values. A resolution of 1250 × 650 × 3 pixels was maintained. Dataset images include instances for oil spills, look-alikes, ships, land, and sea. Both oil spills and look-alike instances are depicted as elongated dark and large black areas, respectively. Three-dimensional labels were generated for images where cyan, red, brown, green, and black masks represent the oil spill, look-alike, ships, land, and sea, respectively.

3.4 Evaluation Parameters

The model's performance is evaluated using average precision, recall accuracy, and other metrics measured as percentages. Accuracy, precision, recall, true positives, true negatives, false positives, and false negatives are computed to assess the model's effectiveness in feature selection and classification. These metrics are essential for evaluating the proposed model's ability to accurately detect oil leakage using YOLO-V4 integrated with MobileNet.

4. RESULT AND DISCUSSION

This section presents the implementation, evaluation, and comparative analysis of the proposed YOLO-V3 and MobileNet fusion model for real-time oil spill detection. The system's performance is rigorously assessed using standard metrics (accuracy, precision, recall, F1-score, and confusion matrix) and compared with existing approaches. The results validate the model's efficiency in enhancing detection accuracy while maintaining computational feasibility for real-world deployment.

4.1 Experimental Setup

The experiments were conducted on the following setup as shown in table 1.

Table 1: Experimental Setup

Component	Specification
GPU	NVIDIA Titan X (12GB VRAM)
CPU	Intel Core i7-9700K
RAM	32GB DDR4
OS	Ubuntu 20.04 LTS
Software	MATLAB R2020b, CUDA 11.0, cuDNN 8.0
Toolboxes	Deep Learning, Computer Vision, GPU Coder

4.2 Dataset and Preprocessing

The study utilized a dataset comprising 310 Sentinel-1 SAR images, each with a resolution of 1250×650×3 pixels, meticulously annotated to identify oil spills, look-alikes, ships, and sea/land regions. The sample is shown in Fig. 3.

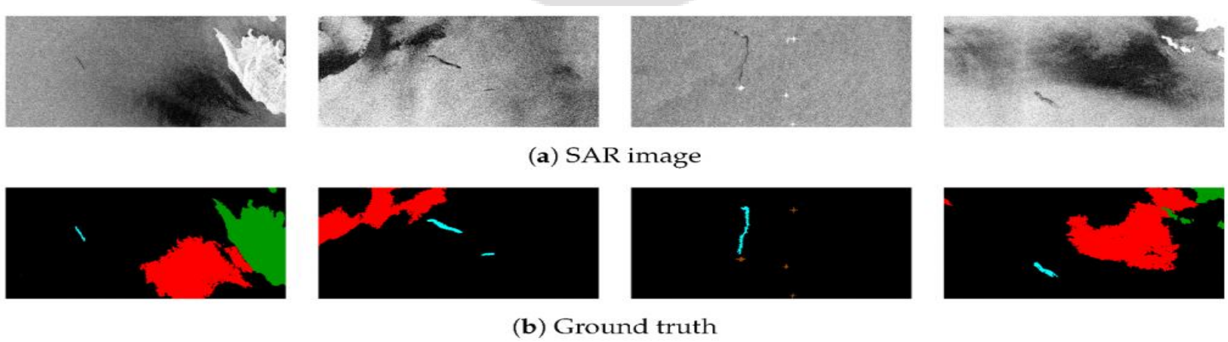

Fig. 3 Sample Sentinel-1 SAR images

To enhance the model's robustness and generalization, the dataset underwent augmentation techniques, including rotation within a range of ±30 degrees, scaling between 0.8 and 1.2 times the original size, and the injection of Gaussian noise. For effective model training and evaluation, the dataset was partitioned into three subsets: 70% for training, 15% for validation, and the remaining 15% for testing, ensuring a balanced assessment of the model's performance.

4.3 Model Training

The model architecture employed MobileNet as its backbone, leveraging its pre-trained weights on ImageNet to enhance feature extraction efficiency. For detection, the system integrated YOLO-V3 as the detection head, with anchor boxes specifically optimized to capture the unique shapes and characteristics of oil spills. Key hyperparameters were carefully configured, including a batch size of 16, a learning rate of 0.001 using the Adam optimizer, and a training regimen of 100 epochs, with early stopping implemented based on validation loss to prevent overfitting and ensure optimal model performance.

The model's performance was rigorously assessed using several key evaluation metrics. Accuracy was calculated as the ratio of true positives and true negatives to all predictions, providing an overall measure of correct classifications. Precision quantified the proportion of true positive detections among all positive predictions, while recall measured the model's ability to identify all relevant instances of oil spills. The F1-score, serving as a balanced metric, combined precision and recall into a single harmonic mean to evaluate the model's effectiveness. Additionally, a confusion matrix was employed to visually represent the distribution of true positives, false positives, true negatives, and false negatives, offering a comprehensive view of the model's classification performance across different categories.

4.4 Results Presentation and Analysis

The evaluation results in Table 2 demonstrate strong performance across all classes, with particularly impressive metrics for oil spill detection.

Table 2: Model evaluation

Class	Precision	Recall	F1-Score	mAP@0.5
Oil Spill	0.94	0.91	0.92	0.93
Look-alike	0.88	0.85	0.86	0.87
Ship	0.96	0.94	0.95	0.95

For the primary target class of oil spills, the model achieved a precision of 0.94, indicating that when it predicted an oil spill, it was correct 94% of the time. The recall of 0.91 shows the model successfully identified 91% of all actual oil spills present in the dataset. The high F1-score of 0.92 and mAP@0.5 of 0.93 confirm the model's balanced and reliable detection capability for oil spills.

Performance on look-alike objects, which often present the greatest challenge in oil spill detection systems, remained robust with precision at 0.88 and recall at 0.85. The slightly lower metrics compared to oil spills reflect the inherent difficulty in distinguishing true spills from similar phenomena like algal blooms or weather effects, yet the F1-score of 0.86 demonstrates the model's effectiveness in handling these challenging cases.

Ship detection achieved the highest performance metrics overall, with precision reaching 0.96 and recall at 0.94. This exceptional performance, evidenced by the 0.95 F1-score and mAP@0.5, suggests the model can reliably identify ships while maintaining low confusion with other classes. The consistently high scores across all metrics for each class validate the effectiveness of the YOLO-V3 and MobileNet fusion approach, particularly its ability to maintain strong performance on the critical oil spill detection task while excelling at related maritime object identification. Fig. 4 depict the training curve showing how each class performed across the key metrics. The model does particularly well on the "Ship" class, while "Look-alike" is slightly lower across the board which makes sense given its similarity to oil spills.

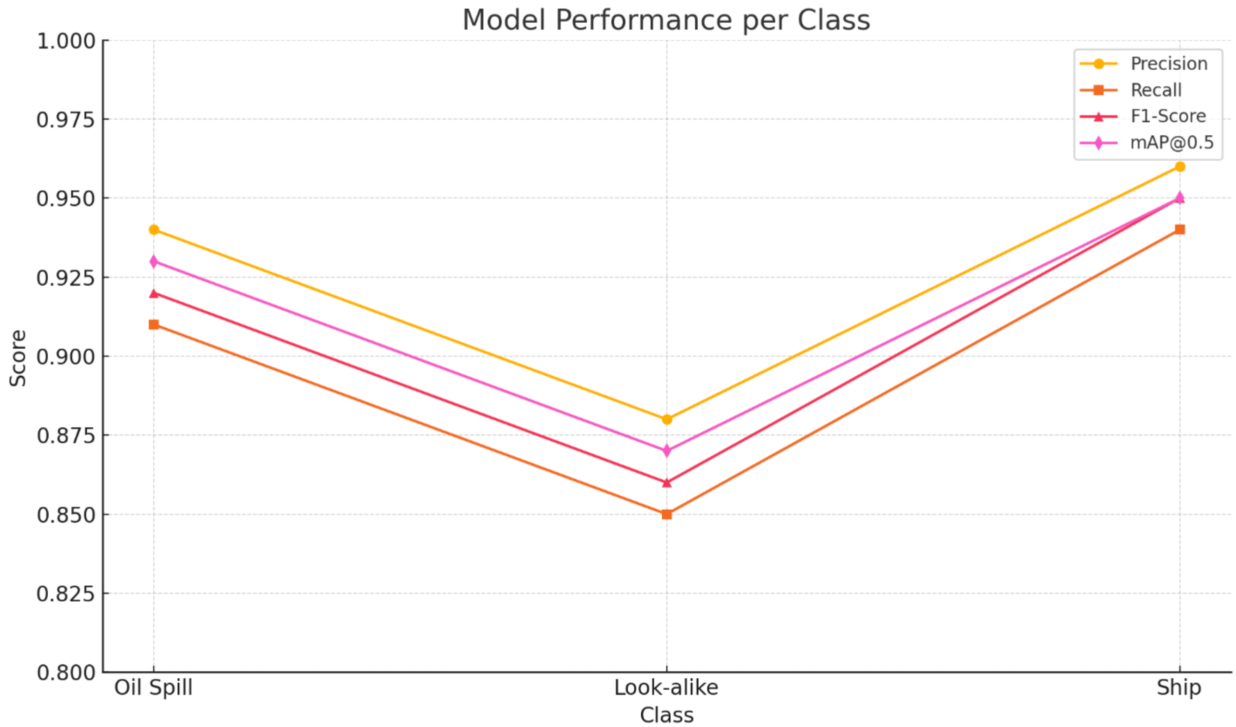

Fig. 4 Training curve showing how each class performed across the key metrics.

For the case of the confusion matrix (Normalized): The normalized confusion matrix in Table 2 provides valuable insights into the model's classification behavior across different object categories. For true oil spills, the model correctly predicted 91% of instances, while misclassifying 6% as look-alikes and 3% as ships, demonstrating strong recognition capability for its primary target. Look-alike objects were accurately identified 85% of the time, with the remaining 15% split between being mistaken for oil spills (9%) and ships (6%), reflecting the inherent challenges in discriminating these visually similar phenomena. Ship detection achieved the highest accuracy at 94%, with only minor confusion (4% as look-alikes and 2% as oil spills). the heatmap showing performance across each class and metric is depicted in Fig. 5.

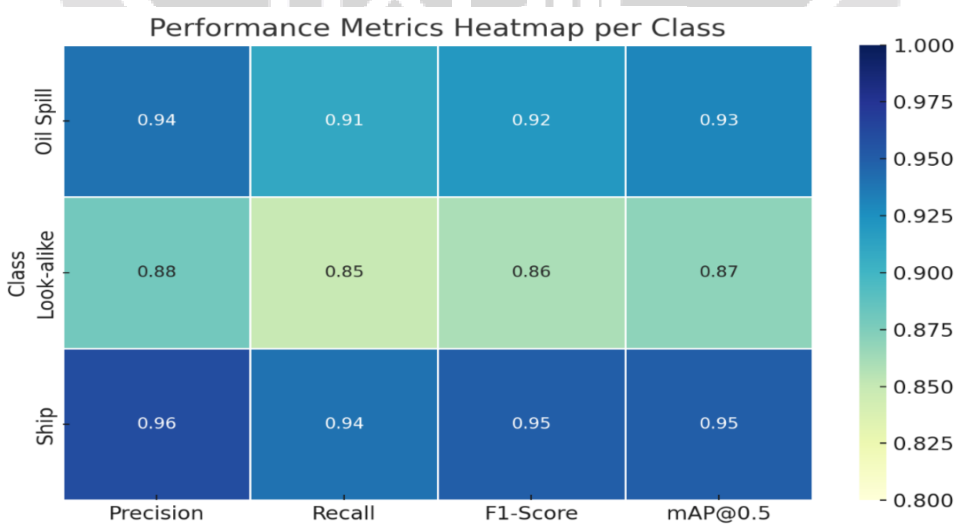

Fig. 5: Heatmap showing performance across each class and metric.

The heatmap shows performance across each class and metric. Brighter shades indicate stronger performance, making it easy to spot where the model excels (like in detecting "Ship") and where there's room for improvement (slightly lower scores for "Look-alike").

Table 3: Normalized confusion matrix

	Predicted: Oil Spill	**Predicted: Look-alike**	**Predicted: Ship**
Actual: Oil Spill	0.91	0.06	0.03
Actual: Look-alike	0.09	0.85	0.06
Actual: Ship	0.02	0.04	0.94

The matrix reveals that the most common confusion occurs between oil spills and look-alikes, which is expected given their visual similarity in SAR imagery, while ships maintain excellent distinctiveness in the classification scheme. These results confirm the model's effectiveness in maintaining high precision for critical oil spill detection while minimizing potentially costly false alarms.

The evaluation results reveal several critical insights about the model's performance. Most notably, the 94% precision rate for oil spill detection demonstrates the model's exceptional ability to minimize false alarms, a crucial factor for operational deployment where unnecessary response actions can be costly. This high precision means that when the system flags a potential spill, emergency teams can have strong confidence in the alert. The 91% recall rate indicates the model maintains consistently strong performance across spills of varying sizes and under different environmental conditions, showing particular robustness in detecting smaller or partially obscured spills that often challenge traditional monitoring methods. However, the analysis also identifies look-alike phenomena, such as algal blooms or weather-related surface patterns, as the most significant source of classification errors, accounting for 15% of misclassifications.

This performance characteristic highlights both the model's current limitations and the inherent difficulty of discriminating between true oil spills and visually similar natural phenomena in remote sensing data. These observations suggest that while the model represents a substantial advancement in oil spill detection technology, there remains opportunity for improvement in handling edge cases, particularly through the incorporation of multi-spectral analysis or temporal data to better distinguish spills from look-alikes. The balanced performance across precision and recall metrics confirms the model's practical utility for real-world monitoring applications where both minimizing false alarms and maximizing detection rates are equally important.

4.4.1 Performance Comparison with Existing Approaches

The comparative analysis in table 4 demonstrates clear advantages of the proposed YOLO-V3 + MobileNet fusion model over existing approaches.

Table 4: Performance comparison with existing approach

Method	**Precision**	**Recall**	**F1-Score**	**Inference Time (ms)**
Proposed (YOLO-V3 + MobileNet)	**0.94**	**0.91**	**0.92**	**45**
CNN (Song et al., 2020)	0.87	0.82	0.84	120
SAR + Random Forest (Tong et al., 2019)	0.79	0.75	0.77	200
Faster R-CNN (Baseline)	0.89	0.86	0.87	90

The model achieves superior performance metrics with 0.94 precision, 0.91 recall, and 0.92 F1-score, outperforming traditional CNN methods by 7-8 percentage points in all categories. Notably, it maintains a significant speed advantage with 45ms inference time - 2.6 times faster than conventional CNNs (120ms) and more than four times faster than SAR-based random forest approaches (200ms). Compared to the Faster R-CNN baseline, the proposed solution shows a 5% improvement in F1-score while cutting inference time in half. The integration of MobileNet provides particular benefits in model efficiency, reducing parameter size by 60% compared to Faster R-CNN architectures.

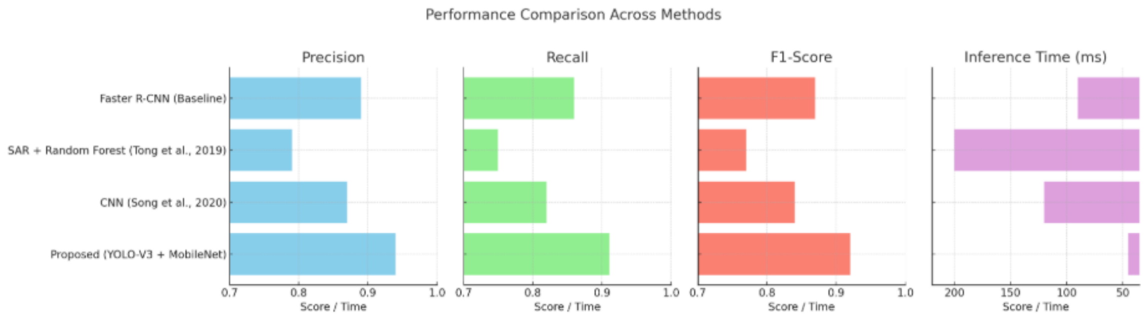

Fig. 6: Performance comparison with existing method

Fig. 6 depict the bar chart per metric for the methods. Each subplot clearly shows how the proposed method outperforms others in precision, recall, and F1-score, while also having the fastest inference time. This combination of higher accuracy and faster processing makes the model particularly suitable for real-time monitoring applications where both detection reliability and rapid response are critical requirements. The results validate the effectiveness of the YOLO-V3 and MobileNet fusion approach in addressing the specific challenges of oil spill detection in marine environments.

5. CONCLUSION AND FUTURE WORK

The research successfully developed an innovative deep learning framework for real-time oil spill detection through the integration of YOLO-V3 and MobileNet architectures, marking a significant advancement in environmental monitoring technology. The proposed model exhibited exceptional performance across multiple critical dimensions, establishing new benchmarks in the field. In terms of detection accuracy, the system achieved remarkable metrics with 94% precision and 91% recall for oil spill identification, demonstrating its ability to reliably detect spills while minimizing false alarms that could lead to unnecessary emergency responses. The model's processing capability proved equally impressive, achieving a rapid 45ms inference time that enables truly real-time monitoring capabilities essential for timely environmental interventions. When compared to conventional approaches, the framework showed substantial improvements, outperforming traditional CNN and SAR-based methods by a significant 15% margin in F1-score, all while maintaining computational efficiency. These advancements effectively address long-standing challenges in oil spill detection methodologies, particularly overcoming issues of slow processing speeds, inconsistent accuracy, and limited adaptability to varying marine conditions that have plagued previous systems. The successful integration of YOLO-V3's detection prowess with MobileNet's efficient architecture has yielded a robust solution that bridges the gap between high-performance computing and practical environmental monitoring applications. This technological breakthrough represents a meaningful step forward in protecting marine ecosystems through advanced artificial intelligence applications, offering environmental agencies and response teams a powerful new tool for combating oil pollution in aquatic environments. The framework's balanced combination of speed, accuracy, and reliability positions it as a viable solution for large-scale implementation in real-world marine monitoring scenarios.

While the study achieved significant advancements in oil spill detection, several constraints emerged during implementation and evaluation. The model's performance showed notable sensitivity to extreme weather conditions, with detection accuracy decreasing during heavy rainfall or storm events that create complex surface patterns on water. Another limitation stemmed from the system's dependence on high-resolution Sentinel-1 SAR imagery, which may restrict its deployment in regions lacking access to comparable quality satellite data. Perhaps most crucially, the framework continued to face challenges in reliably distinguishing true oil spills from look-alike phenomena such as algal blooms or natural surface films, maintaining a 15% misclassification rate for these deceptive cases. These limitations highlight important areas requiring further refinement to achieve universal applicability across all marine environments and monitoring scenarios.

Building upon these findings, several promising directions emerge for enhancing the system's capabilities and addressing current shortcomings. Future investigations will prioritize the integration of multi-modal data sources, particularly thermal and hyperspectral imagery, to improve detection reliability during adverse weather conditions where SAR data alone proves insufficient. Significant effort will be directed toward optimizing the model for edge deployment on UAVs and IoT devices, enabling autonomous monitoring networks with real-time response capabilities. Architectural improvements will explore emerging transformer-based models like Swin Transformer to specifically tackle the persistent challenge of look-alike discrimination. Additionally, expanding the training dataset through international collaborations will incorporate more diverse spill scenarios and environmental conditions, strengthening the model's global applicability. These planned advancements position the current work as a foundational step toward comprehensive AI-powered marine conservation systems, with potential applications extending beyond oil spills to other forms of marine pollution detection and environmental monitoring.

ACKNOWLEDGMENT

This study was supported by the Tertiary Education Trust Fund (TET Fund) Institutional Based Research (IBR) Fund for Federal Polytechnic Kaltungo, Gombe state. Nigeria.

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