RESEARCH TITLE: AI-ASSISTED ENVIRONMENTAL MONITORING IN THE NIGER DELTA: A LIGHTWEIGHT DEEP LEARNING APPROACH FOR OIL SPILL AND MANGROVE DAMAGE DETECTION

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ABSTRACT

Environmental degradation in the Niger Delta—driven by oil spills, mangrove dieback, and water contamination—threatens biodiversity, public health, and livelihoods. Recent work demonstrates that artificial intelligence (AI) and Earth Observation can detect mangrove degradation and oil spill impacts at scale, while broader reviews highlight AI's transformative role in habitat monitoring and biodiversity analysis. Industry perspectives also point to AI-powered leak detection and predictive maintenance as promising tools for pollution reduction. Building on this evidence, this research proposes a lightweight, field-ready image classification system that integrates community-sourced images, low-altitude UAV captures, and satellite chips to detect oil spills and mangrove damage under low-resource constraints. The project benchmarks compact convolutional models (MobileNetV2, EfficientNet-Lite) and explores robustness strategies for domain shift, with explainable AI overlays to build trust. A field pilot in Ogoniland validates performance, usability, and community impact. The outcome is an open, reproducible pipeline enabling near real-time monitoring for communities and regulators, with pathways for scaling across coastal ecosystems.

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1. Introduction

1.1 Background and motivation

- Ecological urgency: The Niger Delta's mangrove forests and wetlands face chronic stress from oil infrastructure leaks, artisanal refining, and waste discharge, resulting in canopy loss, soil toxicity, and fisheries decline.

- Monitoring gap: Traditional monitoring relies on incident reports and infrequent surveys, missing early signals and under-serving remote communities.

- Technological opportunity: AI and remote sensing can turn heterogeneous imagery—smartphones, drones, satellites—into timely, actionable insights suitable for low-connectivity contexts.

1.2 PROBLEM STATEMENT

- Core challenge: Detecting oil spills and mangrove degradation from diverse, noisy images captured across devices, seasons, and sites, while ensuring reliability in low-resource environments.

- Operational constraints: Limited bandwidth, intermittent power, and scarce expert annotators demand compact models, offline capabilities, and efficient labeling strategies.

1.3 RESEARCH SIGNIFICANCE

- Societal value: Empowers communities to document and escalate environmental harm, supporting remediation and accountability.

- Scientific value: Advances robust, compact computer vision for ecological monitoring under domain shift.

- Policy relevance: Provides evidence streams for regulators and NGOs to prioritize interventions.

2. LITERATURE REVIEW/BACKGROUND SECTION

Recent studies have demonstrated the effectiveness of AI and Earth Observation in detecting mangrove degradation and oil spill impacts in the Niger Delta (O'Farrell et al., 2025). Broader reviews highlight AI's transformative role in environmental monitoring, including habitat assessment and biodiversity analysis

(Chisom et al., 2024). Industry experts also advocate for AI-powered leak detection and predictive maintenance to reduce pollution (Oguntona, 2020). These findings underscore the potential of AI-driven tools to support ecological protection in vulnerable regions—yet few systems are designed for low-resource, community-led deployment. This research addresses that gap by developing a lightweight, field-ready classification system tailored to the realities of the Niger Delta.

2.1 AI in environmental monitoring

- Scope: Convolutional neural networks (CNNs) and emerging transformer models have achieved strong performance in habitat classification, species detection, and ecosystem health assessment.

- Relevance: Reviews underscore the role of AI in scaling conservation workflows, improving detection sensitivity, and enabling decision support in the field.

2.2 Earth Observation for oil spill detection

- Findings: Studies using radar and multispectral data demonstrate detection of mangrove mortality linked to oil exposure and proximity to oil infrastructure in the Niger Delta.

- Implication: Satellite indicators can complement ground imagery, offering spatial context and cross-validation for local detections.

2.3 Community-centric monitoring systems

- Approaches: Participatory sensing frameworks harness smartphones and low-cost UAVs, emphasizing usability, feedback loops, and trust.

- Lessons: Tools must accommodate variable image quality, provide interpretable outputs, and function offline with delayed synchronization.

2.4 Gaps in current research

- Under-addressed: Lightweight, field-ready pipelines validated in West African coastal ecosystems; strategies for domain shift across devices and seasons; and human-in-the-loop labeling that scales with community participation.

- This work: Bridges these gaps by integrating community, UAV, and satellite data into a unified, explainable, and deployable system.

3. RESEARCH OBJECTIVES AND QUESTIONS

3.1 Main objectives

- O1: Curate a high-quality, labeled dataset from community photos, UAV captures, and satellite chips.

- O2: Benchmark compact models (MobileNetV2, EfficientNet-Lite, ViT-tiny) for accuracy, latency, and memory footprint.

- O3: Improve robustness via augmentation, calibration, and light-weight test-time/domain adaptation.

- O4: Deploy an offline-capable app with explainability and conduct a field pilot in Ogoniland.

3.2 Research questions

- RQ1: How accurately can lightweight models classify oil spill, mangrove damage, healthy mangroves, and clean water across devices and seasons?

- RQ2: Which augmentation and domain adaptation methods most effectively mitigate domain shift in low-resource settings?

- RQ3: What deployment configuration (on-device, edge, or cloud) best balances latency, reliability, and cost for rural Nigerian contexts?

- RQ4: How do explainability overlays influence user trust and decision-making among community monitors?

4. METHODOLOGY

4.1 Data collection and annotation

- Sources:

- Community imagery: Smartphone photos collected via app with consent and optional GPS/time metadata.

- UAV captures: Low-altitude orthomosaics over target corridors to resolve oil sheen, stressed canopies, and shoreline residue.

- Satellite chips: 224–512 px crops from open imagery aligned to incident locations to provide context.

- Label schema:

- Classes: oilspill, mangrovedamage, mangrovehealthy, cleanwater; expandable to include shoreline residue or vegetation recovery.

- Annotation: Dual-annotator labeling with adjudication; active learning to surface uncertain samples for expert review.

- Quality control:

- Data hygiene: De-duplication, leakage checks, and device/season stratification.

- Agreement: Track inter-annotator agreement and refine guidelines iteratively.

4.2 Model architecture and training

- Backbones:

- MobileNetV2 / EfficientNet-Lite0/1: Baselines for on-device feasibility.

- **ViT-tiny (distilled):** Comparative transformer under tight compute budgets.

- **Training setup:**

  - **Loss and imbalance:** Cross-entropy with class weights or focal loss if minority classes underperform.

  - **Augmentation:** Color jitter, blur, JPEG compression, weather/lighting shifts, rotations; mixup/cutmix for regularization.

  - **Optimization:** AdamW or SGD with momentum; cosine decay or ReduceLROnPlateau; early stopping with best-weight restore.

  - **Calibration:** Temperature scaling or focal loss tuning to improve confidence reliability.

  - **Robustness:** BatchNorm statistics recalibration and test-time augmentation; optional lightweight adapters for domain adaptation.

- **Explainability:**

  - **Grad-CAM/Score-CAM:** Heatmaps overlaid in-app to validate that predictions focus on oil sheens, canopy stress, or turbidity patterns.

4.3 Evaluation metrics

- **Core metrics:** Accuracy, macro-F1, per-class F1, AUROC.

- **Reliability:** Expected Calibration Error (ECE) and reliability diagrams.

- **Diagnostics:** Confusion matrices and error taxonomies (e.g., oil sheen vs. sunglint).

- **Robust tests:** Cross-site validation (train on A/B, test on C), device-specific and seasonal holdouts.

4.4 Deployment strategy

- **Architecture:**

  - **Offline-first client:** Streamlit and Android wrapper with queued submissions; on-device inference using TorchScript or TFLite for small models.

  - **Edge gateway:** Optional Raspberry Pi/NVIDIA Jetson at community hubs for batch inference.

  - **Cloud API:** For heavier models or retraining cycles, syncing when connectivity allows.

- **Model ops:**

  - **Versioning:** Data/model version control; reproducible seeds and experiment tracking.

  - **Export:** .pth and TorchScript/TFLite artifacts with model and data cards.

  - **Monitoring:** Telemetry on latency, failure cases, and drift (opt-in, privacy-preserving).

5. PRELIMINARY WORK

5.1 Prototype overview

- System: MobileNetV2-based classifier integrated into a Streamlit app; supports image upload and displays class probabilities and Grad-CAM overlays.

- Data: Seed dataset from curated samples representing oil sheen, mangrove canopy states, and clean water.

5.2 Early results

- Feasibility: Successful local inference with low latency on CPU; clear separability for strong signals (e.g., thick oil sheen vs. clean water).

- Usability: Positive informal feedback on interface clarity and explanation overlays.

5.3 Lessons learned

- Domain shift: Performance degrades with poor lighting, motion blur, and device heterogeneity—necessitating targeted augmentations and calibration.

- Label ambiguity: Borderline cases (algal bloom vs. oil sheen) require expert adjudication and additional context (e.g., UAV angle, polarization, or multispectral hints).

6. Expected outcomes

6.1 Technical contributions

- C1: A robust, compact classification pipeline optimized for low-resource deployment.

- C2: Empirical study of augmentation and adaptation techniques under real-world domain shift.

- C3: Open dataset (de-identified), codebase, and reproducible training scripts with detailed model/data cards.

6.2 Community impact

- I1: Faster community reporting and verification of spills and damage.

- I2: Evidence for engaging regulators and operators on remediation timelines.

- I3: Capacity-building through training of local monitors and youth groups.

6.3 Scalability and replicability

- S1: Portable to other coastal ecosystems (e.g., mangroves in the Gulf of Guinea).

- S2: Extensible to tasks like severity grading and change detection.

- S3: Modular integration with EO pipelines for spatial prioritization.

7. Work plan and timeline

7.1 Phase breakdown

- **Phase 1 (Months 1–2):** Protocols, ethics, data pipeline setup; seed dataset; annotation guidelines.

- **Phase 2 (Months 3–4):** Baseline training and benchmarks; error analysis; calibration.

- **Phase 3 (Months 5–6):** Robustness experiments (augmentation, adaptation); ablation studies; explainability validation.

- **Phase 4 (Months 7–8):** Field pilot in Ogoniland; usability testing; failure analysis; iteration.

- **Phase 5 (Months 9–10):** Final model; documentation; open release; manuscript and policy brief.

7.2 Milestones

Phase	**Key deliverables**
1	Ethics approvals, data schema, initial labeled set, active learning loop
2	Benchmark report (accuracy, F1, latency), confusion matrices, calibration curves
3	Robustness gains documented; best-practice augmentation/adaptation recipes
4	Pilot report: latency, usability (SUS), user trust, field error taxonomy
5	Public repo, dataset/model cards, preprint, community workshop materials

8. ETHICAL CONSIDERATIONS AND RISK MANAGEMENT

8.1 Data privacy and consent

- **Consent-first:** Clear opt-in for image collection; anonymize PII; coarsen GPS where required.

- **Data governance:** Secure storage, role-based access, and community oversight for local data.

8.2 Bias and fairness

- **Sampling balance:** Stratify by site, season, and device to reduce bias.

- **Fairness checks:** Compare performance across communities and devices; remediate with targeted data collection.

8.3 Mitigation strategies

- **Ambiguity handling:** Route low-confidence cases for expert review; flag for additional evidence (e.g., follow-up imagery).

- **Connectivity constraints:** Offline queueing and periodic sync; on-device inference fallback.

- **Model drift:** Periodic re-training with new labeled data; monitor confidence and error patterns.

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