AI and IoT-Driven Framework for Monitoring and Restoring of Mangrove Ecosystem Health in Coastal Sri Lanka

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***Abstract*—Mangrove ecosystems in Sri Lanka are critical for coastal protection, biodiversity, and carbon sequestration, but face increasing threats from anthropogenic activities and climate change. Traditional monitoring methods often lack the precision and speed required to detect early stage degradation. This study proposes an AI- and IoT-driven framework for monitoring and restoring mangrove ecosystem health in Sri Lanka, based on the global applications of AI, IoT, and Unmanned Aerial Vehicles (UAVs) in mangrove conservation. Findings show that AI techniques such as deep learning, IoT sensors, and UAVs have shown global success in species classification, degradation detection, and high-resolution monitoring. However, Sri Lanka still lacks an integrated AI- and IoT-based system for its mangrove ecosystems. Key gaps include limited localized AI models, poor technological integration, and a lack of real-time monitoring frameworks. To address these gaps, this study proposes a Sri Lanka-specific smart monitoring framework that integrates UAVs for canopy imaging, IoT sensors for root-level data, and AI analytics for real-time anomaly detection and informed decision-making. The four-layered architecture emphasizes data acquisition, secure transmission, machine learning, and an interactive dashboard for real-time monitoring. A phased implementation strategy and recommendations for community engagement, cross-sector partnerships, and policy integration are also provided. With careful piloting and stakeholder collaboration, this framework can transform mangrove conservation efforts in Sri Lanka from reactive to predictive, data-driven ecosystem management.**

Keywords*—*Mangroves, Artificial Intelligence (AI), Internet of Things (IoT), Unmanned Aerial Vehicles (UAVs), Environmental monitoring, Ecosystem restoration, Coastal Sri Lanka

I. INTRODUCTION

Mangrove ecosystems are critical blue carbon habitats that provide a range of ecosystem services, including shoreline stabilization, carbon sequestration, habitat provisioning, and water quality regulation [1], [2]. In Sri Lanka, mangroves cover key coastal zones, such as Puttalam, Batticaloa, and Trincomalee, and support the livelihoods of thousands through fisheries, storm protection, and eco-tourism [3], [4]. Despite their ecological and socio-economic value, these ecosystems are increasingly threatened by anthropogenic pressures such as illegal aquaculture, urbanization, and pollution, as well as climate-induced stressors such as sea-level rise and salinity intrusion [5], [6].

Conservation and restoration initiatives in Sri Lanka have historically relied on community-based approaches and periodic satellite assessments [7]. However, these methods often fall short in detecting early degradation at the root or soil level, where changes in salinity, pH, or waterlogging can severely impact mangrove health before canopy-level symptoms appear [8]. Consequently, restoration efforts tend to be reactive rather than preventive and lack the precision required for long-term ecosystem management.

Recent global advancements in smart environmental monitoring have offered promising alternatives. Technologies such as AI, IoT, and UAVs have enabled real-time, high-resolution, and multilayered environmental assessments across Asia, Africa, and Latin America [9], [10], [11]. AI-driven tools can classify mangrove species, detect anomalies, and model degradation risks using machine learning algorithms like YOLOv5 and ResNet [12], [13]. IoT-based sensors provide continuous monitoring of critical indicators such as salinity, water level, and soil temperature [14], [15], whereas UAVs offer flexible, high-resolution imaging for canopy health analysis [16], [17].

However, these innovations remain underutilized in Sri Lanka. Most initiatives have yet to integrate root-to-canopy sensing, predictive analytics, or context-specific AI training using local datasets [18], [19]. This disconnect reveals a significant research and implementation gap, particularly in building scalable and adaptive monitoring systems that are aligned with the country's ecological and infrastructural realities. To contextualize the significance of mangrove ecosystems and the urgency for smarter monitoring methods, Table. I. summarizes the key aspects of mangroves globally and highlights the specific ecological, economic, and conservation contexts in Sri Lanka.

The following research questions (RQs) guided this analysis:

RQ1 – How can IoT and AI technologies be integrated to monitor both root-level and canopy-level mangrove health in real time?

RQ2 – What methods can detect early signs of mangrove stress through sensor and image data?

RQ3 – How effective is the proposed system when applied to the Sri Lankan mangrove ecosystems?

TABLE I. SUMMARY OF GLOBAL AND SRI LANKAN CONTEXTS OF MANGROVE ECOSYSTEMS

Category	Key Points	Sri Lanka-Specific Insights	References
Definition & Importance	Salt-tolerant forests in tropical intertidal zones covering ~137,000 km² globally across 123 countries. Store 4–5× more carbon/km² than terrestrial forests	~16,000–20,000 ha remaining 24 true species, including *Rhizophora* and *Avicennia*	[20], [21]
Ecological Value	Support 30% of tropical coastal fish species. Reduce wave energy by 50–90%	63 fish species rely on Puttalam Lagoon 3× higher yields near healthy mangroves	[22], [23]
Economic Value	Ecosystem services worth $33k-$57k/ha/year globally. Growing ecotourism and sustainable products	Mangrove honey: 12 tons/year 58% of coastal communities depend on mangrove resources	[4], [7]
Major Threats	Global decline rate: 0.13%/year. Aquaculture and shrimp farming cause 38% of losses. Climate change & salinity intrusion rising	40% lost since 1980s 214 ha converted to shrimp farms 62% in north show salinity stress	[2], [24]
Monitoring Gaps	Most studies rely on satellite only data without ground validation <5% use integrated AI/IoT/UAV-based systems	Only 3 UAV studies published (2019–2024) No national real-time monitoring system	[25], [26]

Accordingly, the main objectives are to: (1) explore global applications of AI, IoT, and UAVs in mangrove monitoring; (2) analyze real-world conservation and restoration efforts using these technologies; (3) identify research and implementation gaps, particularly in Sri Lanka; and (4) propose an integrated, locally relevant smart monitoring framework.

The rest of this paper is organized as follows. Section II describes the methodology. Section III presents the findings across five thematic areas. Section IV discusses the technological and contextual gaps. Section V outlines the proposed national monitoring framework. Section VI concludes with the key contributions of this work.

II. METHODOLOGY

This study followed the PRISMA framework (Preferred Reporting Items for Systematic Reviews and Meta-Analyses). The process was designed to ensure transparency, reproducibility, and critical rigor in evaluating global applications of AI, IoT, and UAV technologies for mangrove ecosystem monitoring and restoration, and their relevance to Sri Lanka. The four phases of the process Identification, Screening, Eligibility, and Inclusion are illustrated in Fig. 1.

A. *Formulation of Search Strings*

Search strings were constructed to capture the intersection of mangrove ecosystem health and smart technologies. Boolean operators combined keywords such as "mangrove ecosystem," "coastal wetland," "AI OR machine learning," "IoT OR smart sensors," and "UAV OR drone." For example, query: *("mangrove" OR "coastal wetland") AND ("AI" OR "machine learning" OR "deep learning")* AND ("IoT OR smart sensors") AND ("UAV OR drone"). This ensured coverage of both technical (AI/IoT) and ecological (mangrove health/restoration) dimensions while maintaining relevance.

B. *Selection of Databases and Search Engines*

This study relied primarily on Google Scholar, selected for its broad multidisciplinary coverage and open access to peer-reviewed journals, conference papers, and technical reports. While specialized databases such as IEEE Xplore, ScienceDirect and MDPI can provide more targeted results, access limitations made Google Scholar the most practical choice. Its inclusive scope ensured both the ecological context of mangroves and the technological aspects of AI, IoT, and UAV applications were captured. To reduce the risk of missing relevant works, additional studies were identified through reference tracing and expert suggestions. The review period was set from 2010–2025, and all records were managed using Zotero for organization and duplicate removal.

C. *Screening Process*

The search produced 7,996 records, plus 15 from reference tracing. After duplicates were removed, 1,996 records remained for title and abstract screening. Of these, 1,696 were excluded as irrelevant. The remaining 300 full texts were reviewed in detail, and 255 were excluded for reasons such as lack of AI/IoT/UAV focus, no mangrove relevance, or insufficient methodological detail. Finally, 45 studies were retained for synthesis, as shown in the PRISMA diagram.

D. *Eligibility Criteria*

Studies were included if they focused on mangroves or coastal ecosystems, applied AI, IoT, or UAV technologies, and were peer-reviewed publications from 2010–2025 with clear methodological detail. Exclusions applied to non-English works, pre-2010 papers, purely theoretical discussions, or abstracts lacking full methods.

E. *Data Extraction and Categorization*

From each study, data were extracted on research location, applied technologies (AI model, IoT sensor type, UAV payload), monitoring level (root, canopy, or integrated), performance metrics such as accuracy or F1-score, and relevance to Sri Lanka was extracted and tabulated. To structure analysis, studies were grouped into five themes: species identification, degradation detection, restoration planning, real-time monitoring, and predictive modeling.

III. RESULTS

The global application of AI, IoT, and UAV technologies in mangrove monitoring has significantly advanced the capabilities of environmental conservation initiatives. These innovations have enabled real-time data collection, high-resolution spatial analysis, and predictive modeling key aspects previously unattainable through traditional monitoring methods.

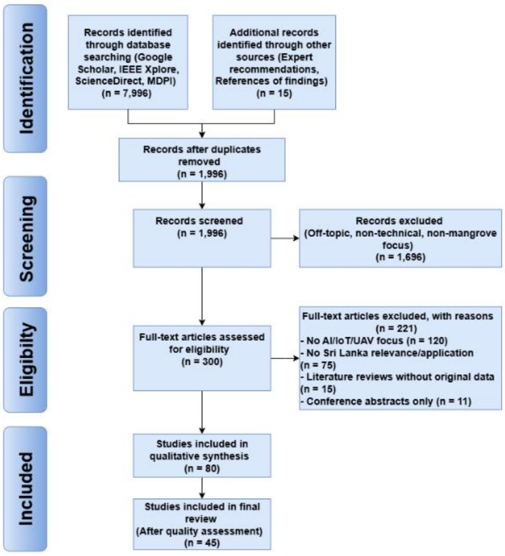

Fig. 1. PRISMA Diagram

A. *Use of UAVs in Mangrove Mapping and Monitoring*

UAVs have emerged as indispensable tools for high-resolution, low-altitude imaging in mangrove conservation. Abu Bakar et al. [9] examined the role of UAVs in mapping blue carbon ecosystems, emphasizing their cost-effectiveness, image precision, and flexibility across terrains. UAVs equipped with RGB, multispectral, and LiDAR sensors are increasingly used to assess canopy density, detect species diversity, and monitor phenological changes [27]. For example, Lim et al. [28] demonstrated the use of YOLOv5 algorithms in detecting mangrove species from UAV imagery with high accuracy, while Thoha et al. [29] confirmed UAV viability for species classification in Southeast Asia.

Moreover, UAV-based mapping has been successfully deployed in countries like Indonesia and Brazil to monitor restoration sites and evaluate aboveground biomass recovery [23], [30]. These applications highlight UAVs' utility not only for monitoring but also for guiding restoration decisions.

B. *IoT Applications for Root-Level Monitoring*

IoT-based sensor networks complement UAV imaging by capturing below-canopy environmental data. These networks enable continuous monitoring of variables such as soil salinity, pH, temperature, and water levels all crucial indicators of mangrove health [14], [15]. Studies by Hussen Hajjaj et al. [31] and Asghar et al. [32] show that low-cost, solar-powered IoT systems can be tailored for harsh coastal environments, improving data reliability while minimizing maintenance costs.

Li et al. [33] introduced a real-time edge-AI system that processes sensor data locally, reducing dependence on cloud infrastructure and increasing responsiveness. Such advancements could be adapted to Sri Lanka's remote coastal zones, where connectivity issues hinder centralized data transfer.

C. *AI for Image Classification and Predictive Modeling*

AI, particularly deep learning, has redefined environmental monitoring. Several studies apply Convolutional Neural Networks (CNNs) and segmentation algorithms (e.g., UNet++, ResNet, SVM) to classify mangrove species, detect anomalies, and estimate biomass [12], [18]. Fu et al. [34] combined SVM and Res-UNet to map spatiotemporal changes in Chinese mangrove forests, achieving high classification accuracy across time series imagery.

In Sri Lanka, few applications exist beyond basic land cover mapping [7], highlighting a gap in AI adoption for predictive ecosystem analysis. Globally, integrated systems are also being used for early warning systems predicting stress events such as salinity spikes or dieback before visible degradation occurs [10], [35].

D. *Integrated Framework*

While each technology offers unique benefits, global best practices emphasize integration. Integrated frameworks utilize UAV imagery for canopy analysis, IoT sensors for ground conditions, and AI models for real-time analytics [11], [26]. For instance, Lomeo and Singh [36] developed a cloud-based dashboard combining UAV imagery and AI analytics for Southeast Asia, enabling visualization, alerts, and policy planning.

These integrated solutions allow for multi-layered analysis connecting root-level stress indicators with canopy-level responses, thus enabling holistic ecosystem management. In contrast, Sri Lanka's existing systems remain fragmented and manual, with minimal sensor deployment and no unified AI-driven platform [8].

E. *Regional Gaps and Adaptation Potential*

While countries like the UAE, India, and China lead in smart mangrove monitoring, Sri Lanka lags behind in adopting these technologies. Kodikara et al. [3] emphasized that many restoration projects in Sri Lanka fail due to poor site selection and lack of baseline ecological data. As a result, conventional replanting often leads to low survival rates [4].

The existing literature suggests that integrating AI–IoT–UAV systems can help bridge this gap. However, a localized approach is necessary. For instance, datasets trained on global imagery often fail in the Sri Lankan context due to differences in mangrove species, canopy structure, and seasonal variability [19], [37]. This reinforces the need for country-specific datasets and real-time monitoring protocols.

IV. DISCUSSION

The study reveals that the integration of AI, IoT, and UAV technologies has revolutionized mangrove monitoring and restoration across many countries. However, translating these advancements into the Sri Lankan context reveals a significant gap in readiness, infrastructure, and localized application. This section critically examines these gaps and outlines key areas for adaptation.

A. *Technological Readiness and Adoption Gap*

While many countries such as China, India, and the UAE have adopted smart environmental technologies for mangrove management [12], [27], Sri Lanka remains dependent on manual surveys, coarse-resolution satellite imagery, and intermittent monitoring efforts [3], [7]. Most national projects emphasize replanting or awareness without integrating real-time monitoring systems. This limits timely decision-making and reduces the success of restoration efforts [38].

The absence of UAV-based surveillance and root-level IoT sensor networks in Sri Lanka prevents holistic monitoring. Global research confirms that UAVs can effectively track canopy health and species structure, while IoT systems provide critical soil data such as salinity and waterlogging early indicators of ecosystem degradation [9], [31]. Sri Lanka's delay in deploying these technologies represents a missed opportunity for early detection and mitigation.

B. Data Infrastructure and Model Localization

Many international case studies assessed have benefited from open-access environmental datasets and AI models trained on local imagery and conditions [34]. However, in Sri Lanka, such datasets are scarce. As a result, AI models developed elsewhere often underperform when applied to Sri Lankan landscapes due to different species compositions, ecological patterns, and weather variability [36].

This lack of localized training data also inhibits predictive modeling and early warning capabilities an essential advantage of AI-based systems. Without annotated drone imagery or sensor feeds, Sri Lanka cannot fully leverage deep learning models such as ResNet or UNet++ for tasks like species classification, change detection, or degradation forecasting [35].

C. Policy, Funding, and Collaboration Barriers

Another critical gap is the policy and institutional framework. While global projects often involve cross-sector partnerships between universities, governments, and tech firms [11], [26], Sri Lanka lacks cohesive national strategies to promote digital conservation. Studies have noted poor funding, weak inter-agency collaboration, and low technical capacity as limiting factors [39], [40].

This institutional inertia slows innovation and hinders sustainable implementation. For instance, pilot projects using IoT or UAVs in Sri Lanka are often isolated, lacking integration into national monitoring systems or long-term conservation plans [8]. Furthermore, policies do not currently incentivize the use of smart tools in ecosystem monitoring or provide funding mechanisms to scale them.

D. Need for Community-Driven Smart Monitoring

Another insight from global studies is the growing role of community participation in deploying and maintaining AI-IoT systems [37], [41]. Sri Lanka has a strong history of community involvement in coastal restoration, but this has yet to be translated into tech-enabled monitoring frameworks.

Training local users to operate UAVs, interpret dashboard data, or manage sensor nodes could significantly improve adoption, sustainability, and trust in such systems. Local ownership also enhances the resilience of systems in the face of political or financial shifts, ensuring that conservation does not stall due to institutional bottlenecks.

Based on that, selected studies were categorized under three core RQs to assess the technological scope and impact of AI, IoT, and UAV applications. Table. II. compares key studies according to the addressed RQs, technology used, monitoring focus (root vs. canopy), and key outcomes relevant to mangrove ecosystem monitoring.

V. PROPOSED FRAMEWORK FOR SRI LANKA

To address the critical technological, data, and policy gaps highlighted in Section 4, we propose a localized, AI- and IoT-integrated smart monitoring and restoration framework tailored to Sri Lanka's unique coastal ecosystems. This framework is informed by global best practices (e.g., China, UAE, Indonesia) and adapted to the socio-technical realities of Sri Lanka.

A. Rationale for a Localized Framework

The fragmented nature of existing mangrove conservation efforts in Sri Lanka dominated by manual assessments and disjointed data collection demonstrates the urgent need for a centralized, real-time monitoring platform [3], [42]. The suggested system would enable a shift from reactive restoration to predictive, data-driven management. While similar architectures using UAV-LiDAR and deep learning models have shown success in China and India [27], [35], these technologies require calibration to suit Sri Lanka's ecological conditions and institutional landscape.

TABLE II. LITERATURE COMPARISON TABLE

RQ	Reference	Technology Used	Monitoring Scope	Findings
RQ1: IoT-AI Integration				
	[42]	Satellite, AI analytics	Global canopy-level	Advanced mapping lacks root-level focus
	[27]	UAV, LiDAR, Hyperspectral	3D structure & biodiversity	Fine-scale species assessment
	[31]	IoT sensors	Hydrology (root-level)	Flood risk reduction prototype
	[36]	CNN, Google Earth Engine	SE Asia canopy	90% F1-score (canopy only)
RQ2: Stress Detection				
	[12]	UNet++, Sentinel-2	Canopy stress (UAE)	87.8% mIoU, +2,061 ha mapped
	[43]	Multispectral UAV	Canopy degradation	Identified stress indicators
	[16]	RGB drones	Species-level ID	Cost-effective but canopy-limited
	[44]	Tiny U-Net, FPGA	Oil spill detection	79% IoU, low-power edge AI
RQ3: Real-World Validation				
	[11]	AI + IoT sensors	Marine ecosystems	Needs mangrove adaptation
	[19]	Mamba model, Sentinel-2	Global canopy	87.8% mIoU (outperformed CNN)

B. System Architecture

As illustrated in Fig. 1., the framework is structured into four interconnected layers, allowing scalability and interoperability:

1) Layer 1: Data Collection

This layer deploys in-ground IoT sensors to measure salinity, water level, pH, and temperature at root level. These are placed in vulnerable estuarine and lagoon ecosystems, particularly in Negombo, Puttalam, and Batticaloa. Simultaneously, UAVs equipped with multispectral and RGB cameras perform scheduled flights to capture high-resolution canopy imagery. Together, these modalities enable root-to-canopy ecosystem visibility.

2) Layer 2: Data Transmission and Storage

IoT and UAV data are transmitted in real time via LoRaWAN or cellular networks to a cloud-based repository, allowing scalable data access. The cloud platform is equipped with encryption and access management to ensure secure multi-stakeholder use [26].

3) Layer 3: AI-Driven Analytics

Machine learning models such as YOLOv5 for species detection and ResNet for canopy classification analyze incoming data. Custom models trained on Sri Lankan datasets detect anomalies (e.g., sudden salinity increases) and forecast degradation risks [12], [17]. Over time, this layer becomes smarter through iterative learning based on labeled data and community feedback.

4) Layer 4: Decision Support Dashboard

A web-based and mobile-friendly dashboard visualizes spatial data, health metrics, and alert triggers. Coastal managers, environmental NGOs, and local communities can access real-time updates, thresholds, and historical comparisons. Alerts are triggered when defined environmental thresholds are crossed, prompting field inspections or interventions.

C. Key Features of the Framework

The proposed system includes core elements that align with the environmental and social conditions of Sri Lanka, as shown in Table. III.

TABLE III. KEY FEATURES OF THE PROPOSED FRAMEWORK

Feature	Description
Real-Time Root–Canopy Monitoring	Combines UAV and in-ground IoT data for full-spectrum ecosystem assessment [27]
AI-Powered Decision Support	Automated image and sensor data analysis for early stress detection [42]
Scalable and Modular	Can be replicated in different districts or estuaries across Sri Lanka [45]
Community Engagement	Local stakeholders can access data and receive alerts through mobile apps [43]
Policy Integration	Dashboards support data-driven conservation planning and impact evaluation [11]

D. Pilot and Scaling Strategy

A phased rollout is recommended

- Phase 1: Pilot Deployment in Negombo and Puttalam to validate data flow, community usability, and model accuracy.
- Phase 2: Calibration and Optimization, including training AI models on localized UAV and IoT data.
- Phase 3: Scaling across major mangrove zones like Trincomalee, Batticaloa, and Hambantota, in collaboration with the Forest Department and local universities.

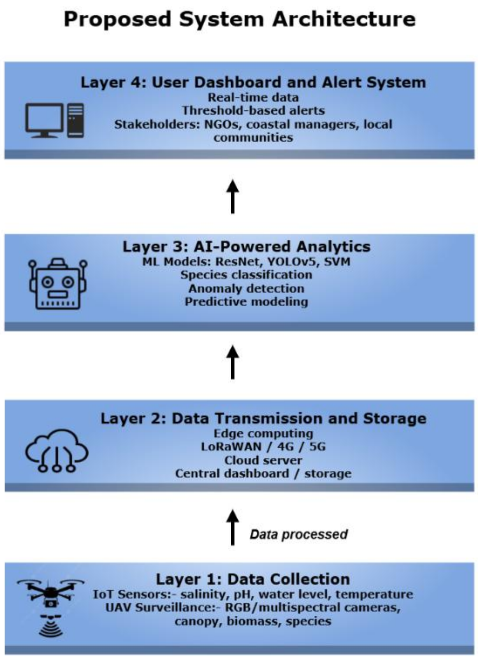

Fig. 2. Proposed AI-IoT-UAV-Based System Architecture for Smart Mangrove Monitoring in Sri Lanka.

E. Sustainability and Local Ownership

To ensure longevity, the framework prioritizes

- Open-source development for AI models and dashboards to reduce vendor lock-in.
- Community training for data collection and sensor maintenance [41].
- Public–private partnerships for funding, cloud infrastructure, and capacity building [39].

VI. CONCLUSION

This study examined how AI, IoT, and UAV technologies can enhance mangrove ecosystem monitoring, with particular focus on their application in Sri Lanka. The global review demonstrated that these tools are increasingly successful elsewhere, yet their integration and adaptation to local conditions remain limited in Sri Lanka. To address this gap, a framework was proposed that unifies root-level IoT sensing, UAV-based canopy monitoring, and AI-driven analytics into a coherent system for ecosystem health assessment. This design responds directly to the absence of localized datasets, limited cross-technology integration, and weak institutional coordination identified in the literature. By synthesizing global best practices and aligning them with Sri Lanka's ecological and infrastructural context, the framework provides a pathway for shifting from reactive monitoring toward predictive, proactive conservation. Future advancements will depend on creating open-access national datasets, implementing pilot projects to validate the framework in coastal sites, and strengthening collaboration between researchers, policymakers, and communities. In summary, the smart integration of AI and IoT is not merely a technological option but a necessary step to transform mangrove conservation in Sri Lanka into a proactive and predictive system for sustaining ecosystem health.

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