



ARGUS

Aerial Reconnaissance for Ghost-Net Understanding and Salvage

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Abstract

Each year, 114,640 additional pounds of nets accumulate in the Northwestern Hawaiian Islands. These “ghost” nets are typically lost fishing nets that have devastating impacts on marine life and ecosystems, catching onto reefs and killing animals who become entangled. Ghost nets can also end up wound around ship propellers, which can damage mechanical operations and endanger the crew.

Current removal efforts have difficulty locating ghost nets, often relying on limited-accuracy satellite data, buoys that may drift away from the net, and human divers. Once underwater, ghost nets can become almost indistinguishable from coral reefs, making them challenging to identify from satellite imagery alone. To address this challenge, our proposed solution is Aerial Reconnaissance for Ghost-Net Understanding and Salvage (ARGUS) that utilizes Uncrewed Aircraft Systems (UAS) equipped with specialized sensors and AI analysis to identify ghost nets and alert cleanup organizations.

Using satellite imagery, our system targets ocean areas in the Northwestern Hawaiian Islands with historical ghost net activity and plastic pollution. Ground control deploys scout UAVs that fly a surveying pattern and scan the ocean using Red, Green, Blue (RGB) and Near-Infrared (NIR) sensors to flag potential ghost nets. Confirmation UAVs equipped with Short-Wave Infrared (SWIR) sensors then fly to the flagged areas, verify that the targets are ghost nets, and send coordinate and video data back to ground control for additional verification if necessary. Finally, local marine debris cleanup organizations are notified of the ghost net locations and go out to remove them.

By continuously circling the net as it moves and sending live coordinates, ARGUS’s confirmation UAVs allow for targeted, efficient net removal, reducing diver and crew search time. As a result, ARGUS can lead to healthier habitat and aquatic conditions for marine life, as well as safer voyages for ships.

Section 1. Introduction

About 5.7% of fishing nets are estimated to be lost worldwide each year [1], adding approximately 78,000 km² of ghost nets to the world's oceans. This severe form of marine pollution heavily damages marine ecosystems and kills thousands of marine animals every year [2]. The problem is especially significant in the Great Pacific Garbage Patch, where at least 46% of the floating plastic mass is made up of fishing nets that can entangle marine life [3]. These statistics demonstrate that ghost nets are not an isolated issue but rather a massive global problem that threatens marine life worldwide. The most concerning aspect is that rather than being static pollution lying on the ocean floor, ghost nets continue to trap and kill marine animals long after they are lost [4]. Because many of these nets are made from non-biodegradable materials, they can remain in the environment for years, continuously damaging marine ecosystems.

The current system to search for ghost nets is an extensive and costly process. The first step often uses satellite imagery to scan marine areas for deviations from standard water images. These deviations appear as dark spots or areas with heavy marine pollution, which can indicate that a ghost net might be present. Then, a manual human analysis of the satellite imagery is conducted to verify the potential presence of a ghost net. Once the ghost net is confirmed, a search and recovery team is sent out to remove the ghost net from the ocean. If the ghost net is physically located, ocean divers are deployed to cut up these nets and haul them onto the search boat. After this, search crews return to shore and send these ghost nets to recycling or trash facilities. It can take up to two weeks from detection to processing the net at a designated disposal facility.

The current system has many inefficiencies, including in the human analysis portion of the process. These problems lead to an increased probability of false alerts, missed alerts, and incorrect classification of ghost gear type [5]. Human analysis is also time-consuming, meaning that nets can drift far from where they once were by the time humans have identified them.

Similarly, current satellite imagery does not provide sufficiently accurate and timely location information. This means that hours may be spent by search and recovery crews physically searching for the ghost net without a precise location to navigate to. This locational generalization leads to increased operating costs and time spent, reducing the number of ghost nets that can be extracted.

Furthermore, biofouling of ghost nets that have been on coral reefs for about 12 months causes algae and other marine organisms to build up. As a result, nets become heavier and sink deeper into the reef until it is challenging to differentiate the nets from the reef. It is also difficult or impossible to detect nets that have been submerged more than one meter below the ocean surface using satellite imagery since the nets' spectral signatures are rapidly lost. Alternatively, even when nets are detected, they often drift before cleanup crews can arrive, meaning that boats have to spend extra time locating where the nets are.

The proposed Aerial Reconnaissance for Ghost-Net Understanding and Salvage (ARGUS) incorporates two additional steps to the ghost-net identification process to improve detection accuracy and range. Satellite imagery continues to be used to identify general areas that may contain ghost nets, but scout and confirmation UAS will search and verify ghost nets in the ocean from lower altitudes with the use of machine learning. With this system, crews are sent only when ghost nets have been confirmed, reducing unnecessary strain on resources.

Section 2. Background

PROPOSED PILOT IMPLEMENTATION

The UAS's implementation will begin with smaller and shallower areas around heavily polluted coastlines to validate systems while also using the collected data to enhance the accuracy and performance of the machine learning model. This may mean using only two scout UAVs and one confirmation UAV initially. From this point, gradual expansion farther into the ocean would be possible. As our machine learning model continues to improve, its detection frequency and accuracy are expected to increase as well, allowing ARGUS to target more difficult or remote areas. Additionally, as the efficiency of ghost net removal increases, fixed-base operations will expand to more locations in order to extend the range and capabilities of operations. Similarly, when the UAVs are first deployed, they will be heavily monitored by ground crews. However, as more successful operations are completed and confidence in the system increases, the level of ground monitoring can gradually decrease, allowing for more automated operations. The end state of ARGUS would include fully autonomous UAVs that require little to no human monitoring. These UAVs would be capable of detecting ghost nets in the deep ocean and heavily polluted areas, allowing recovery crews to locate and remove ghost nets more efficiently.

Area of Interest

The Northwestern Hawaiian Islands (Fig. 1) were selected as the operating area of focus in this study.

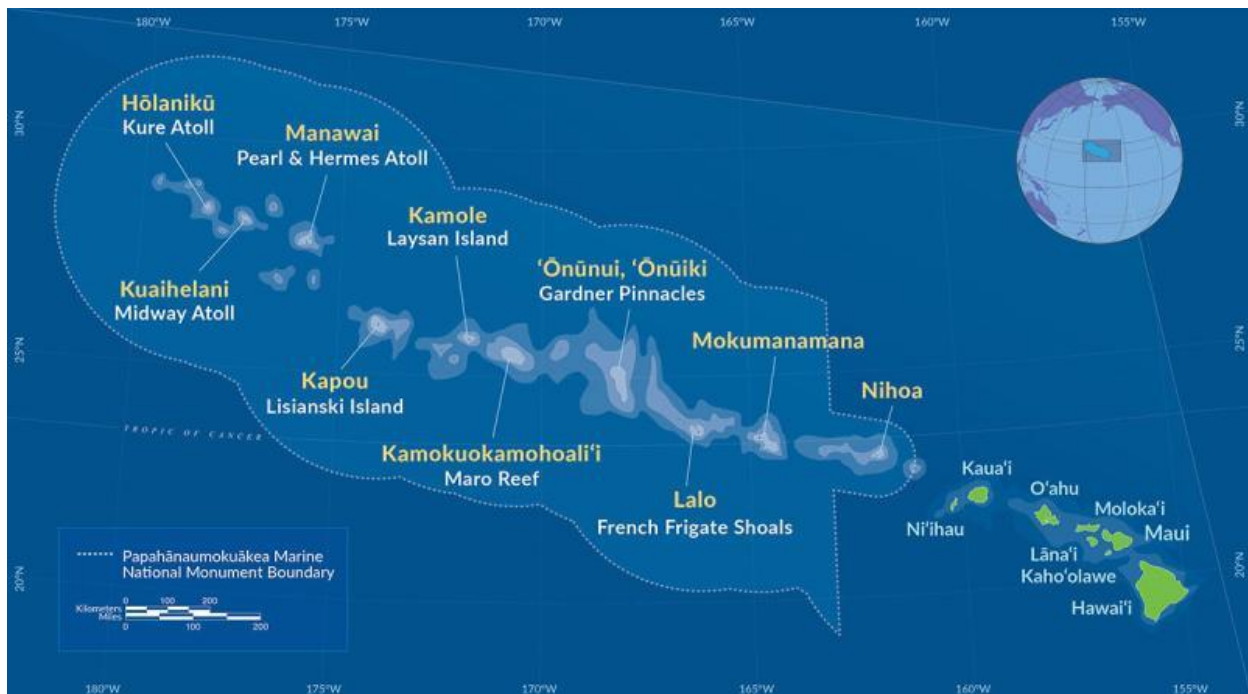


Figure 1. Map of the Papahānaumokuākea Marine National Monument [6]

Other contenders included Australia, New Zealand, Southeast Asia, and the Gulf of Mexico, all of which contain significant marine debris buildup [7]. A major consideration, however, are UAV's wind limitations. The maximum wind speeds that UAV can withstand are up to 40 miles per hour; both the Northwestern Hawaiian Islands and the Gulf of Mexico meet this requirement, with the exception of extreme weather conditions such as hurricanes. Ultimately, the Northwestern Hawaiian Islands were chosen because the Papahānaumokuākea Marine Debris Project voiced in an interview on July 23, 2026 that their main difficulty was the detection of ghost nets, while the Gulf of Mexico's main issue was the actual extraction of the nets. Since the proposed solution focuses on detection rather than extraction, the Northwestern Hawaiian Islands were a better fit.

More specifically, within the Northwestern Hawaiian Islands, the Papahānaumokuākea Marine National Monument is the area of interest, spanning about 140,000 square miles. Every year, an estimated 115,000 pounds of additional ghost nets accumulate in this region alone [8]. It is also an incredibly biodiverse area and home to over 7,000 species, many of which are threatened or endangered — including seals, sea turtles, birds, and plants that exist nowhere else on Earth [9]. Therefore, ghost net removal is crucial to protect these endemic species and habitats [10].

It is important to note that the Federal Aviation Administration (FAA) has an advisory that sets a minimum aircraft altitude of 2,000 feet above noise-sensitive environments such as the Papahānaumokuākea Marine National Monument to avoid scaring birds and harming seals and other marine life. This minimum altitude requirement was considered in the development of ARGUS, as both the confirmation and scout UAVs cruise at altitudes in compliance with the FAA advisory [11].

Section 3. Methodology

Existing models that process satellite imagery will be used to indicate where ghost nets are most likely to be found in the area of interest, and that information will determine where scout UAVs are initially sent. Once a potential ghost net has been detected by a scout UAV at a low-confidence threshold, a confirmation UAV that operates at a high-confidence threshold is sent to verify. Then, if the confirmation UAV confirms a ghost net is there, ground control at a nearby base on shore will stream the live video from the confirmation UAV and override or confirm the presence of a ghost net. Finally, if the net is confirmed, the coordinates will be sent to cleanup organizations while the confirmation UAV continues to circle the object until cleanup divers arrive to retrieve the ghost net. Lastly, there are some post flight processes, including saving quantitative and qualitative data, that will be implemented to improve operations and retrain models.

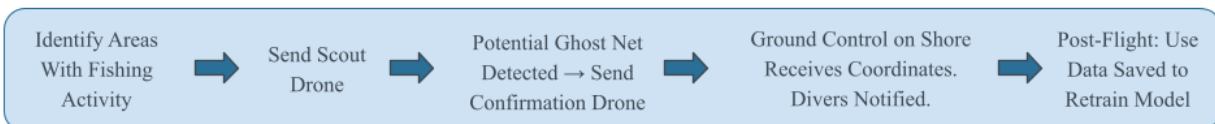


Figure 2. Methodology Overview

Satellite

In order to have an initial idea of where the UAS can begin search operations, satellite imagery will be analyzed using an existing algorithm to determine the general area to send the scout UAVs. The algorithm has an 86% accuracy rate for processing imagery from the Sentinel-2 satellite to find marine pollution [12]. Sentinel-2 contains a Multispectral Instrument (MSI) camera system that includes a short-wave infrared (SWIR) camera, which can detect wavelengths emitted by different substances [13]. Since marine pollution is often made of nylon and polyester, and those materials emit unique wavelengths, the algorithm will evaluate the reflectances and flag groups of pixels to indicate that there may be a potential ghost net there. The scout UAVs will be sent to areas with the most flagged pixels.

The purpose of the UAS is to verify the presence and determine the exact coordinates of a ghost net before notifying divers. Additionally, since the Papahānaumokuākea Marine Debris Project also maps previous ghost nets found, the areas that the organization has extracted the highest number of ghost nets can be another target for the scout UAVs.

Scout UAV

During a mission, the scout UAV is designed to fly approximately 2,800 to 3,000 feet above the ocean. A human operator will define the search area, altitude, safety boundaries, and abort conditions before takeoff. The aircraft then follows the assigned search route and surveys the area for possible ghost nets. Depending on the shape of the region, it may use a lawnmower path for complete rectangular coverage, parallel lines for long and narrow areas, or a spiral pattern around a suspected hotspot [14]. A shared coverage map utilized by all ARGUS UAVs will record the areas already searched. This prevents multiple ARGUS UAVs from rescanning the same area or interfering with one another.

The scout UAV configuration carries an RGB and thermal imaging gimbal, a RedEdge-P multispectral camera for near-infrared imaging, a polarimetric filter for reducing sun glare, and an NVIDIA Jetson Orin Nano for onboard image processing. The purpose of these components is detailed in the Sensor Attachments section.

The scout's detection model uses a low-confidence threshold of 0.20. The low threshold is designed to detect as many actual ghost nets as possible, even if it also produces some false alerts. After the scout identifies a possible ghost net, it records the coordinates and sends selected images and/or a short video to ground control. Line-of-sight radios support nearby operations, while satellite communication can support missions farther offshore. After human review, the coordinates are passed to the confirmation UAV.

Confirmation UAV

The confirmation UAV flies to each marked location and inspects possible ghost nets from a lower altitude of approximately 2,000 to 2,200 feet, allowing for the thin mesh of a ghost net to occupy more pixels in the image. It circles the object while collecting higher-detail imagery and updating the ghost net's locations as it moves with the currents. The confirmation UAV carries an RGB, thermal imaging gimbal, and an NVIDIA Jetson Orin Nano (like the scout UAV) along with an SWIR sensor. At the target, the confirmation UAV performs a stricter test using a confidence threshold of 0.80. This is because the model must be extremely confident that the marine debris is a ghost net. This helps lower the probability that boats and divers will be dispatched to false positives such as driftwood, seaweed, or algae.

If the object passes the confirmation test, the confirmation UAV flies around it using a proposed radius of approximately 400 feet. This is intended to keep the target within view of the confirmation UAV while avoiding inefficient fuel wastage. Since a floating net can continue moving with the winds and currents, the confirmation UAV tracks its position and sends updated coordinates and live video to ground control instead of only reporting the possible ghost net's original location. A human operator reviews the imagery and can confirm or reject the model's findings before boats and divers are notified. Once approved, the live coordinates are sent to cleanup crews so they can travel to the net's current location.

Post-Flight Evaluation and Improvement

In order to improve future operations, a post flight routine will be implemented. Both qualitative and quantitative data will be collected and added to the dataset that is used to train the models. The qualitative data includes both virtual and in-person surveys or interviews of ground control. Questions will be asked to gather feedback on their user experiences and potential interface issues, difficulties, and recommendations. Additionally, images collected during the flight will be added to the dataset. The quantitative data includes coordinates, which are sent live during the operation, and time to complete the mission, as well as the number of accurate and inaccurate findings.

The number of accurate and inaccurate findings will create an accuracy rate, which will give a better understanding of the impact of the project. Additionally, if the images saved reveal a shape of a ghost net that was not previously accounted for, it will be added to the dataset and the models will be retrained. Furthermore, if new machine learning or AI models are found that could potentially be applicable to our model, they will be exercised on the updated training dataset before being tested in real field operations.

Cleanup

Procedures will be established to handle situations when a UAV is physically damaged (e.g., badly hit or rained on). If it is able to return to the base, it will do so, and ground control technicians will work to repair or replace the impacted parts. However, if it is unable to return to base, it will immediately send its own coordinates to ground control, and divers will be sent to retrieve the UAV. Since UAs are costly, hiring divers to retrieve impaired UAs and technicians to repair them is more cost conscious than purchasing replacement UAVs. Additionally, leaving impaired UAs out in the ocean contributes to marine pollution, which conflicts with the principles of this project.

Section 4. System Design, Architecture, and Specifications

UAV SPECIFICATIONS

ARGUS uses two UAVs: a scout for wide-area detection and a confirmation for closer inspection. The Shield AI V-BAT was selected as the primary scout and confirmation UAV because it combines the efficiency of being a fixed-wing aircraft with vertical take-off and landing capabilities [15]. This feature allows the UAV to operate without a runway and launch from a coastal station or any small clearing. The same UAV aircraft type is used for both scout

and confirmation in ARGUS to simplify maintenance and facilitate aircraft substitutions (only need to change some sensors).

The V-BAT uses a JP-5 heavy-fuel engine and has a published endurance of more than twelve hours. However, ARGUS uses a more conservative nine-hour mission window, which leaves approximately twenty-five percent of the aircraft's endurance in reserve for changing weather conditions and unexpected delays. Its endurance would still need to be confirmed through testing after all the sensors are installed, though, because payload weight can affect the UAV's endurance.

The aircraft has a maximum payload capacity of 40 pounds, a wingspan of 12.5 feet, and a maximum takeoff weight of 165 pounds. It can operate from a 15-by-15-foot launch area and can be prepared for flight by a two-person team in under 30 minutes. These characteristics make this aircraft suitable for long maritime operations while keeping deployment requirements relatively small. Line-of-sight radios support nearby operations, while satellite communication can support missions farther offshore. These operations would still require the appropriate FAA authorization. Additionally, the V-BAT is produced by a U.S. company, meaning it complies with federal security and procurement requirements [16].

Before flight, ground control will inspect the V-BAT's airframe, ducted fan, landing gear, fuel, camera payload, and data links. Then, after flight, the aircraft will be dried and checked for salt exposure. Ground control will also download the mission and maintenance logs. The workflow and turnaround are depicted in Figure 3.

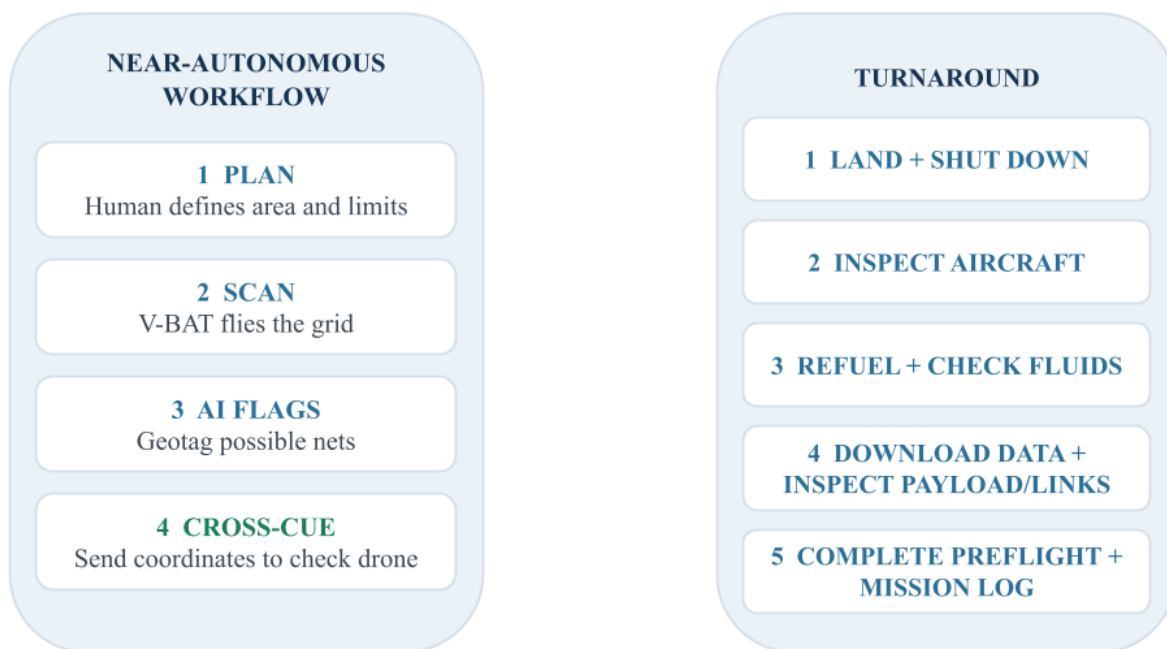


Figure 3. V-BAT Workflow and Turnaround

Sensor Attachments

As mentioned in previous sections and shown in Table 1, the scout and confirmation UAVs will utilize several of the same sensors, including the RGB camera, thermal IR sensor, polarimetric filter, and NVIDIA Jetson. However, the scout UAV will also incorporate a multispectral and NIR sensor, while the confirmation UAV will utilize an SWIR hyperspectral

sensor. Both camera types will be mounted on the underside of the UAV. More details will be covered in the subsequent sections.

Table 1. Scout and confirmation drone sensors

Sensor	Band	Detection	Tier
Multispectral (+ NIR)	700–1,000 nm	Water is black in NIR, floating objects stay bright	Scout
RGB camera	Visible (400–700 nm)	Visible shape/color of surfaced mesh	Scout/Confirm
Thermal IR	LWIR (7–14 μm)	Optional for nighttime	Scout/Confirm
Polarimetric	Visible	Removes sun glint to reveal surface object	Scout/Confirm
NVIDIA Jetson	N/A	Runs detection models onboard	Scout/Confirm
SWIR hyperspectral	1,000–2,500 nm	Polymer absorption through wavelength detection	Confirm

Scout

The scout UAV utilizes several technologies because no single sensor can reliably identify every possible ghost net. Together, the suite of sensors provide object-to-water contrast, visible shape and color, optional thermal imagery, glare reduction, and onboard AI processing as described next.

The multispectral sensor adds near-infrared (NIR) imagery between approximately 700 and 1,000 nanometers. Water absorbs near-infrared light and appears very dark, while many floating objects remain brighter [17]. This contrast makes potential debris easier to separate from the surrounding water. An example selected multispectral sensor is the RedEdge-P Multispectral [18].

The RGB camera records normal visible-light imagery and provides information about an object's shape, color, and surface structure [19]. The selected RGB camera — the Overwatch Gimbal — also includes thermal imaging, which could support future nighttime operations [20].

A polarimetric filter, such as the PolarPro Polarizer Filter, reduces sun glare reflected from the ocean surface [21]. This makes floating objects easier to see.

The NVIDIA Jetson serves as the onboard AI computer [22]. It processes the camera imagery inside the aircraft and runs the detection model in real time. This allows the UAV to transmit important alerts, selected images, and coordinates instead of continuously streaming all of its raw footage over the ocean.

Confirmation

In addition to utilizing several of the same sensors (polarimetric filter, RGB and thermal IR camera) and the same NVIDIA Jetson as the scout UAV, the confirmation UAV will also be equipped with a SWIR hyperspectral sensor. The purpose of this sensor is to detect ghost net materials based on wavelength [23]. An example of a sensor that aligns with these requirements is the Trillium Engineering HD95 SWIR sensor [24]. This is a U.S.-made sensor to comply with the federal government's rules on the purchase of foreign components.

This sensor works by detecting reflected light, particularly because plastics absorb at specific wavelengths that water, algae, and wood do not [25]. Furthermore, different plastics have different signals as shown in Table 2, so hyperspectral software can flag pixels matching those reference spectra.

Table 2. Plastic absorption wavelengths

Plastic	Peak Absorption Wavelength
Polypropylene (PP)	1192, 1394, 1730 nm
Polyethylene (PE)	1201, 1430 nm
Polyester	1130, 1413, 1660 nm
Nylon	Distinct signal

In addition to the SWIR sensor's material detection, shape detection is also important. A segmentation model will validate net morphology like the repeating mesh lattice and water visible through the holes to make sure that both the target's polymer and shape match up to be a ghost net. Using the SWIR sensor, water will show up dark, and floating objects will be bright white or gray, which will help with ghost net identification.

By using an SWIR sensor, cleanup crews will have a better idea that potential ghost nets are made of nylon or other plastics and not just driftwood or algae. The SWIR sensor is utilized for the confirmation UAV because it captures images in more detail, while the multispectral sensor utilized for the scout UAV is less costly and better suited to more general mapping. However, the accuracy of the SWIR sensor will also depend on how deep into the water the ghost net has sunk and the training model as well.

The HD95 SWIR sensor weighs 17 lbs, which is an important factor because the UAV's payload capacity should be able to comfortably accommodate this weight. The SWIR sensor weight is also the reason for having scout and confirmation UAVs that perform different tasks versus simply attaching the heavy SWIR sensor to the scout UAV because that would affect the UAV's endurance and range. The HD95 is expected to reduce the maximum endurance of the confirmation UAV by around 10-20%. The exact reduction percentage would be confirmed during initial test operations. By having separate scout and confirmation UAVs, the former has the potential to survey a larger area and obtain a wider view of potential ghost nets.

Table 3. HD95 specifications and features

Size	10 x 13 in
Weight	17 lbs
Power	35W average; 100W peak consumption
Bandwidth	60 Hz closed loop stabilization
Optics	360° continuous pan; -80°–75° tilt; 132x visible zoom; 40x Mid-Wave Infrared (MWIR) zoom; 1-degree Field of View (FOV) SWIR
Onboard GPS	0.5° total system accuracy; real time geopointing and geolocation

AI-POWERED NAVIGATION AND DECISION SYSTEMS

Reasoning

The machine learning component of the proposed system is designed to address two primary challenges associated with autonomous ghost-net detection: the large volume of imagery gathered during long-duration surveys and the difficulty of distinguishing ghost nets from visually similar floating materials.

Long-endurance aerial surveys generate large quantities of imagery that are impractical to manually review following the mission. The proposed machine learning component would perform this detection during flight to identify candidate objects and send its geographic coordinates. The onboard processing capability is important as the UAS operates on a hierarchical detection pipeline. The machine learning models would operate at different spatial scales that would progressively narrow the search area.

Current aerial detection methods face challenges in object discrimination. Sargassum algae, driftwood, ghost nets, and plastic tarps can be visually distinct at close range but are difficult to distinguish from an aerial perspective. Floating vegetation and other debris can form elongated and parallel structures that resemble netting, while the spectral information can become ambiguous under varying material and environmental conditions [26].

To address this, the system combines both geometric and spectral information. The geometric information would describe the spatial structure and morphology of the object while the spectral information provides information about its material characteristics. The combination of these two components ultimately provides a stronger basis for identifying ghost nets.

Machine Learning Architecture

The proposed machine learning pipeline builds upon existing models rather than developing each component from scratch. The models will operate at three main scales: satellite imagery, scout UAV imagery, and confirmation UAV imagery. Each stage will serve a different function within the overall detection process.

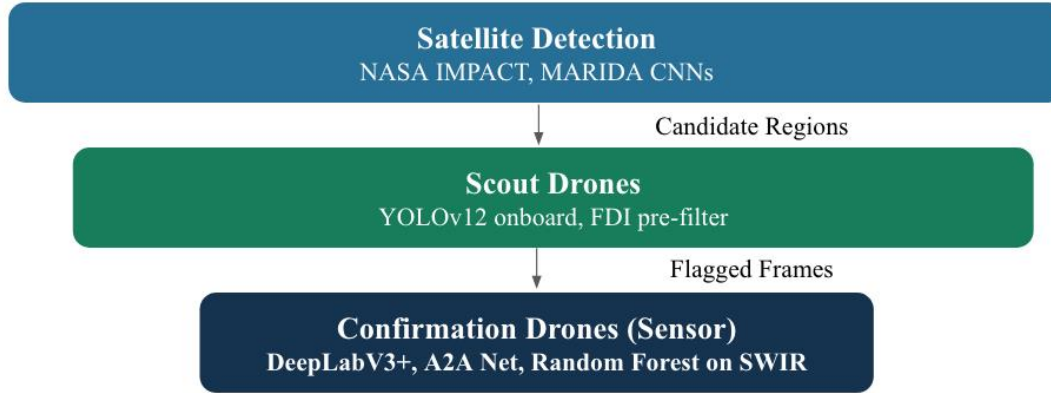


Figure 4. Existing Machine Learning Models

Satellite Identification

At the largest spatial scale, existing marine debris detection approaches can be used to identify initial candidate regions for aerial investigation by UAS. Models associated with NASA IMPACT and MARIDA-based convolutional neural networks (CNN) currently identify marine debris from remote-sensing imagery [27], [28].

The satellite stage is not intended to identify individual ghost nets. Rather, its main purpose is to reduce the geographic search by identifying regions with a higher likelihood of containing relevant marine debris. These candidate regions would then be passed to the UAV aerial survey for the next higher-resolution investigation.

Scout UAV Detection

Within these candidate regions, the scout UAV provides higher-resolution imagery for real-time identification of potential objects [29]. The YOLOv12 family object detector is proposed for onboard detection [30]. A Floating Debris Index (FDI) can serve as the preliminary filter to distinguish areas of potential floating material from predominantly open water before the full detection network is applied.

The scout stage is intended to operate in real time to generate candidate detections while the aircraft is airborne. Each detection will be associated with a geographic location and confidence value that is subsequently passed to the confirmation stage. The scout stage is initially optimized with a low threshold value (0.2), leading to higher recalls. The threshold is intentionally set low at this stage to avoid missing a potential ghost net that would be evaluated in the confirmation stage because missed alerts are consequential in terms of environmental impacts. This threshold can be increased over time as more operations are conducted, more data is gathered, and the model is re-trained and re-tuned.

Confirmation UAV Analysis

The confirmation UAV operates on a smaller spatial scale and therefore acquires more detailed imagery of the candidate objects. At this stage, existing semantic and instance segmentation approaches such as DeepLabV3 alongside the A2ANet detector can be evaluated alongside a Random Forest classifier on the SWIR spectral information [31], [32].

Segmentation is particularly relevant to ghost net identification, as these nets are thin, irregular, and often categorized as string-like. A bounding box would predominately contain

water surrounding the net whereas a segmentation mask would represent the spatial geometry of the net itself. The spectral component provides complementary information by analyzing the SWIR response associated with both the material and surface characteristics of the candidate object [33].

Detection Architecture Summary

Together, the three stages form a hierarchical detection architecture: satellite models initially narrow the scope of the geographic search areas, allowing scouts to be sent out in these regions, identifying candidate objects. From the candidate objects detected, the confirmation system would perform detailed morphological and spectral analysis.

However, these existing models were developed primarily for broader marine debris or remote sensing tasks rather than specifically distinguishing ghost nets from close range aerial views. The proposed methodology would focus on adapting these existing approaches to ghost-net-specific morphology and spectral characteristics.

Table 4. Existing Model Data and Performance

Model	Data	Performance
NASA IMPACT - Single Shot Detector (SSD) with ResNet-101 backbone and Feature Pyramid Network (FPN)	PlanetScope 3 m, RGB + near-infrared (NIR)	Precision 0.78, recall 0.70
Random Forest (spectral and texture features)	MARIDA (Marine Debris Archive), Sentinel-2, 11 bands	IoU 0.69, PA 0.79, F1 0.79
YOLOv12	UAV/ASV/ROV RGB, multimodal debris dataset	mAP@50 0.8354, mAP@50–95 0.7025
A2ANet	RGB: D_six river debris dataset and FloW-Img floating waste benchmark	mAP@0.5 0.841 (D_six)
DeepLabV3 with ResNet50 backbone	GhostNetZero side-scan sonar, grayscale	mIoU 0.739 (Baltic Sea) / 0.685 (Puget Sound)

Metrics: IoU = intersection over union, the overlap between the predicted and actual regions; mIoU = mean IoU across classes; PA = producer's accuracy; F1 = harmonic mean of precision and recall; mAP@50 = mean average precision at an IoU threshold of 0.50; mAP@50–95 = mean average precision averaged across IoU thresholds from 0.50 to 0.95. Values are not comparable across rows as the models were evaluated on different different tasks, sensors, and datasets.

Machine Learning Pipeline

The machine learning pipeline consists of five stages: data collection, image conditioning, morphological labeling, model training, and validation. Each stage addresses a limitation that is associated with adapting the existing marine debris models for the ARGUS design.

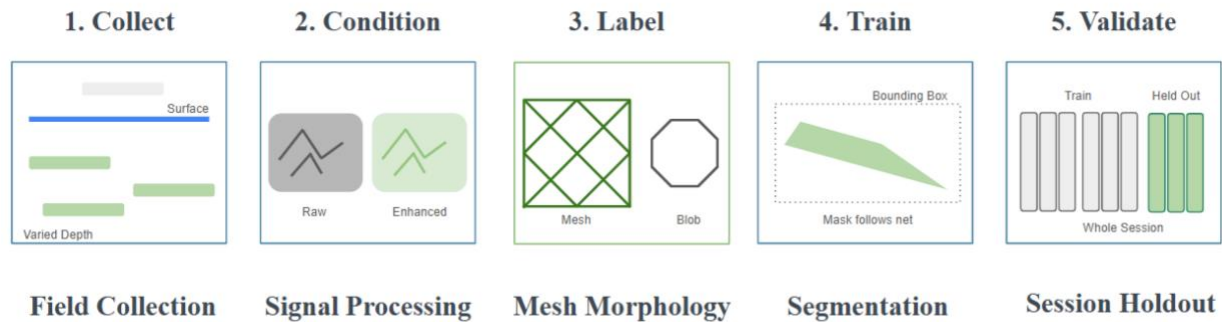


Figure 5. Machine Learning Pipeline

Data Collection

Existing ghost-net datasets provide a useful starting point, but they do not directly represent the sensing conditions of the proposed system. For example, datasets such as GhostNetZero use side-scan sonar to identify ghost nets on the sea floor while ARGUS will rely on aerial optical and SWIR imagery. The differences in viewing angle, object scale, environment background, and spectral information would make a direct application of the existing datasets insufficient for training the proposed model.

To address this limitation, a deployment-based aerial dataset would be developed using known ghost nets that are surveyed under controlled conditions relative to the operating environment. This dataset would have variation in factors such as water depth, fouling, illumination, and background conditions and capture imagery at the operational altitudes at which the scout and confirmation UAVs would operate. Imagery with Sargassum algae and floating plastic debris would also be collected using the same environmental and imaging conditions. This ensures that the models would differentiate between the characteristics associated with ghost nets in the ocean and those of other objects in the marine environment.

Image Conditioning

The collected imagery would undergo conditioning to improve the visibility of the features needed for the detection. The aerial imagery over water can contain noise and variation caused by illumination and environmental conditions. Filtering and signal processing techniques would be used to improve the contrast and enhance the important visual and spectral information that are fed into the models.

The conditioning would need to preserve the physical geometry of the net. The mesh structure, strand arrangement, and relationship between the ghost net and water would be important for distinguishing the ghost net clearly from other debris. Any processing that would distort these characteristics would need to be avoided.

Morphological Labeling

The conditioned imagery would be annotated for ghost-net morphology to distinguish from generic marine debris. Subject matter expertise would be used to identify characteristics that differentiate the ghost nets from other floating materials. Some of the key morphological features that would be used include repeating lattice structure from the mesh, visible water through the openings, and elongated and tangled structures associated with the nets.

The expert-derived characteristics provide the foundational basis for annotation while allowing the machine learning model to be able to identify additional features from the imagery. This combination is important since ghost nets often vary in appearance based on orientation from degrees of entanglement and environmental conditions.

Model Training and Fine Tuning

The existing marine debris models serve as an initial foundation and would be fine tuned using aerial datasets (described in a prior section) to be specialized for ghost net detection. In the confirmation stage, the segmentation models would be relevant since ghost nets are thin, irregular, and string-like.

Conventional bounding boxes would mostly contain water when applied to the thin net, which could limit the spatial information provided to the classifier. By comparison, segmentation identifies the pixels that belong to the ghost net and preserves the geometry that is important for confirmation. These components would be adapted around the polymer and surface conditions that are expected in deployment environments, allowing the spectral information to complement each other.

Validation and Benchmark

The final stage evaluates if the adapted models would be able to generalize beyond the imagery used during training. Rather than randomly dividing individual frames between training and testing sets, collection sessions would be tested for validation. Adjacent frames would contain essentially identical views of the same net, so randomly distributing these frames would introduce temporal and spatial correlation between the training and test sets, inflating performance estimates. Having session-level holdouts would result in a realistic measure of how the system performs on unseen conditions.

The existing published benchmark results would establish the baseline performance for comparing against the adapted models to determine the effectiveness of the fine tuning for ghost nets. This evaluation would emphasize metrics that are important to each stage of the pipeline as missed targets would not be recovered downstream. Precision is important because these high-confidence detections would trigger deployment of limited cleanup crew resources. They would help determine the operating thresholds for the scout and confirmation models.

Challenges and Future Adaptation

Challenges still remain in adapting the machine learning pipeline for operational deployment. First, dataset coverage is limited as existing ghost net datasets do not completely represent the optical and SWIR conditions in the ARGUS concept. The initial Hawaii data provides an important foundation for training and validation, providing a starting point to adapt the models to new environments. Second, the net scale would limit SWIR classification as many of the isolated strands occupy less than a pixel and produce weak spectral responses. The sensor fusion addresses this, allowing the segmentation to capture strand geometry while

spectral information becomes more useful for larger net masses. Finally, the scout recall is critical as a missed alert cannot be evaluated by the confirmation UAV. Having a lower scout detection threshold during training would prioritize scout recall and allow for additional false positives to be filtered out as more operations are conducted, more data is gathered, and the model is re-trained and re-tuned.

SYSTEM INTEGRATION AND INTEROPERABILITY

The proposed ARGUS system is particularly valuable because it can be smoothly integrated into existing operations. Instead of seeking to remake the current ghost-net identification system, ARGUS adds to it to expedite the process so that more ghost nets can be located and retrieved by divers and cleanup organizations.

Ground Control

Ground control personnel are crucial in the ARGUS concept. They include all of the workers at the base that work to make operations possible and include technicians, monitors, and divers.

The ground control technicians work on the hardware aspects of the UAV. For example, if a UAV is rained on or badly hit by a bird or some other object caught in the wind, it will return to the base if possible. If it is unable to return to base and falls into the water, it will be retrieved by divers. After retrieval, the ground control technicians will work to repair the UAV. They are also responsible for regular maintenance of the UAVs.

The ground control monitors images and video that are sent from the confirmation UAV once it detects a ghost net (not continually for energy efficiency). The ground control monitors can analyze the data and override or confirm the detection of a ghost net before notifying divers. As the detection performance of the UAVs increases over time, the ground control monitors can be assigned to other essential tasks.

Divers are tasked with retrieving nets and impaired UAVs. The divers that retrieve the ghost nets are from organizations that specialize in retrieving marine pollution. The divers that retrieve downed UAVs would be unique to this project. These divers would recover any UAVs that fell into the ocean. Retrieving the UAVs is vital because leaving them would add to marine pollution and replacing them would be costly (hundreds of thousands of dollars).

Both the scout and confirmation UAVs perform real-time communications with ground control for efficiency because searching for ghost nets is only feasible during specific seasons since harsh winter weather can make ocean conditions dangerous, and cleanup organizations avoid diving during nesting or pupping seasons for wildlife. For example, the Papahānaumokuākea Marine Debris Project only has 60-90 days per year to find ghost nets through field operations, as endangered monk seals have pupping season from March to August, and avian nesting cycles during the fall and early winter further limit the search period [34]. In addition, since the Papahānaumokuākea Marine National Monument is extremely remote while also covering a large area, with 5,000 square miles of shallow-water coral reefs, cleanup efforts are restricted by travel time and staffing. Therefore, real-time communication is integral to efficient performance and provides divers with exact knowledge of where the confirmation drone is circling at any given time, avoiding additional search time due to drifting.

Failure Modes and Redundancy

Since the scout UAV operates using a low-confidence threshold, the confirmation UAV will inevitably encounter instances where the ghost net is not there. Figure 6 depicts the process that the confirmation UAV takes in this case.

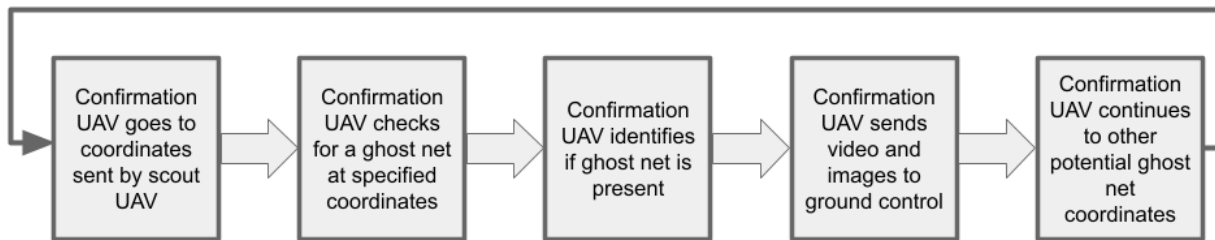


Figure 6. Confirmation Failure Modes and Redundancy

The confirmation UAV goes to coordinates sent by the scout and scans for a ghost net. If it confirms the presence of a ghost net, videos and images are sent to ground control, both for their immediate verification of the ghost net and to be saved for subsequent re-training and re-tuning of the respective models utilized by the scout and confirmation UAVs. Then, the confirmation UAV will continue to the next potential ghost net coordinate in its queue to either locate a net or repeat the false-positive process.

Section 5. Performance Analysis and Discussion

POTENTIAL IMPACTS

Enhanced Identification Efficiency

The ARGUS system makes the identification step of ghost net removal more efficient by reducing the amount of time needed for manual searching. Instead of relying on human analysis of satellite imagery followed by divers and ships checking again for nets that may have drifted away, ghost net removal organizations will be able to travel directly to the located nets. This is achieved through AI analysis of imagery taken by the scout and confirmation UAVs, allowing more information to be processed at once and reducing the amount of time needed to identify ghost nets accurately. Ultimately, the ARGUS system is designed to help search a wider coastal area. Since possible ghost nets can be identified and verified before a cleanup crew is sent, this will lead to more efficient operations by ensuring that cleanup crews are only sent when there is actually a ghost net to remove.

Improved Marine Life and Habitats

Overall, the purpose of more efficient and enhanced identification by the ARGUS system is to facilitate more net removal by cleanup organizations. This will improve the quality of life for marine organisms and create healthier marine habitats. With fewer nets in the ocean, marine life will be less likely to encounter them and be entangled and strangled. Likewise, nets will be less likely to be caught on coral reefs and damage these fragile structures. Additionally, since nets can tangle around propellers and other ship parts, fewer nets in the ocean also means reduced

risk of mechanical damage and failure, creating safer conditions for fishermen, divers, and others who engage in maritime operations.

System Scalability and Operational Flexibility

Although the Northwestern Hawaiian Islands and the Papahānaumokuākea Marine National Monument in particular are the target of the ARGUS concept in this paper, the system may also be utilized in other areas. For example, cleanup organizations in Australia, New Zealand, Southeast Asia, and other areas of the U.S. with ghost net marine pollution could adapt the ARGUS system to fit their specific needs and geographic locations. The proposed system approach could potentially also be utilized to identify other marine debris in addition to ghost nets, such as plastic bags and bottles, lost fishing lines, and other ghost gear.

This project did not address net-cleanup in the Great Pacific Garbage Patch (GPGP) due to there already being cleanup organizations and removal efforts there without as much of a need for net identification, but the system could be adapted for use in the GPGP. If it became necessary to prioritize removal of certain plastics for environmental or time considerations, ARGUS could be used to flag such materials or objects.

Currently, ARGUS is designed to have one scout UAV scan a small section of targeted area to reduce overlap, but future applications may explore using swarms of smaller UAVs to mark initial ghost nets for further investigation. Another potential area of research might be using a scout UAV to transport smaller, more cost-effective UAVs with lower endurances to search for ghost nets.

ARGUS LIMITATIONS

ARGUS has several limitations that would need to be addressed prior to full-scale deployment. It depends on satellite imagery to identify areas where ghost nets are more likely to be found, but it may not show nets that have been submerged or covered by marine organisms. In addition, weather conditions, communication reliability, and the need for human monitoring could limit operations. The machine learning models would also need additional training using aerial images collected under different water, lighting, and environmental conditions to improve their accuracy.

Communication Loss

Communications can become unreliable when UAVs operate far offshore because they may move beyond the range of standard radio signals. If communication is lost, real-time video, telemetry, and GPS updates may be interrupted, making it harder for ground control to monitor the mission. To reduce this risk, ARGUS could use satellite communication (SatCom). The UAVs could also store GPS coordinates and important flight data onboard so that information is not lost during temporary communication interruptions.

Confirmation UAV Bottleneck

The confirmation UAV stage can become a bottleneck because confirmation UAVs have to inspect all possible ghost net detections from scout UAVs. If detections are generated faster than confirmation UAVs can investigate and circle around them until cleanup crews arrive, a queue can form and other potential ghost nets identified by scout UAVs may drift away. More

confirmation UAVs may need to be added to the fleet and/or detections with higher confidence levels may need to be prioritized.

Conclusion

Ghost nets are an extremely significant problem, with 500,000 to 1 million pounds of additional nets accumulating in the ocean per year [7]. The ARGUS system proposed in this paper specifically targets the Northwestern Hawaiian Islands because it is home to many endangered species and high biodiversity and has a high proportion of the global rate of net accumulation at about 115,000 additional pounds per year [8].

That has a devastating impact on marine life since a study found that 4,500 nets kill 2.5 million marine invertebrates, 800,000 fish, and 20,000 marine birds [35]. That is why efficient net removal is essential to protecting marine life and ecosystems.

The proposed ARGUS system begins by using satellite information to narrow the coastal search area. A scout UAV then uses RGB and near-infrared sensors to search widely and mark possible ghost nets. After that, a confirmation UAV uses SWIR imaging to examine each marked object more closely. Live imagery and videos of the potential ghost nets identified by the confirmation UAV are shared with ground crews to confirm. Live locations are then shared by the confirmation UAV circling around the confirmed ghost net to boats and divers to guide cleanup.

ARGUS is designed to reduce the amount of time spent searching for ghost nets by directing crews to stronger leads. The UAVs can cover a wider coastal area than boat crews. Overall, ARGUS searches widely, confirms carefully, and provides useful locations to cleanup crews to make ghost net removal faster and more efficient for the benefit of marine life, ocean habitats, and making maritime operations safer for humans as well.

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