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Doctoral Dissertation

應用混合智慧於海洋生物多樣性資源之管理研究
The Study of Hybrid Intelligence on the Management of Marine Biodiversity Resource

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應用混合智慧於海洋生物多樣性資源之管理研究

（論文中文題目）(Chinese title of PhD dissertation)

The study of hybrid intelligence on the management of marine biodiversity resource

（論文英文題目）(English title of PhD dissertation)

本論文係__陳楊文_(姓名)_D10B45001_（學號）在國立臺灣大學___漁業科學__(系/所/學位學程)完成之博士學位論文，於民國_113_年_5_月_28_日承下列考試委員審查通過及口試及格，特此證明。

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致謝

本論文創新性地結合海洋潮間帶生態監測保育與AI應用，源自於個人一生對海洋的熱愛，也肩負重塑臺灣巴賽民族（Basay）海洋智慧的使命。我出生於臺灣大學校門口前的水源地，從中學懂得搭公車起，就常常偷偷搭車跑到東北角各地海岸浮潛探險，最後停留在三貂角觀察潮間帶生態，一轉眼經過20年。能有此愛海的著迷，相信應該是源自於基因中的記憶，自此開啟追尋海洋民族的根，興起將此海洋的熱愛轉成學術研究的念頭。

本文能成形，須深摯感謝韓玉山教授的鼓勵與不辭辛勞指導，審查委員陳正虔老師、盧道杰老師、張俊偉老師與楊恩誠老師，感謝您們提供敏銳智慧與溫暖的鼓勵與建議，深感榮幸能邀請擔任我博士論文的口試委員。

過去20多年來，家人總是陪同我到三貂角與台灣各海域探索紀錄生態。感謝好友國防醫學院胡智偉助理研究員、新竹實驗中學揭維邦博士、小琉球正好友生態旅舍蔡正男先生、吳松鴻教練與羅東高中劉佳勳老師，以及台灣各地熱愛海洋公民科學的支持，一起探索我們周遭的海洋，分享生命觀察所得，才能讓此論文得以成形。

為了呼應4百年前（1626年5月11日）西班牙人發現紀錄三貂角之舉，我

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嘗試將 AI 與公民科學 CS 所構成的混合智慧 HI 保育架構，加上先前多年持續在三貂角的觀察，做成學術論文「聖杯」獻給這片海陸交接的土地，同時也將三貂角 Cape Santiago 之名列入國際學術文獻中。希望這篇論文能夠激起更多人對臺灣周遭海洋的熱情與研究，最後，將此文獻給摯愛的臺灣與海洋、天上的父母親陳健榮先生與陳楊來春女士、太太曾詩琴、女兒陳鯨、陳翎，永遠愛你們。

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中文摘要

人類對近海資源的利用，由傳統漁業發展至蓬勃的藍色經濟模式，尤其在沿海休閒活動方面特別顯著。然而，當代如人口增長、都市化和氣候變化等環境衝擊已造成潮間帶生態系統顯著的生態影響，需要從科學、社會、經濟、法律等，多元方法進行海岸生態資源的永續管理。在日益增加的旅遊壓力下，小琉球和三貂角馬崗的海岸，面臨了經濟利益與環境保護之間的衝突。因應的海洋保育法尚在進行立法過程，現實存在管理上的窘境，也凸顯了社區自發參與保育倡議的迫切性。本研究探究如何運用 AI 與人之間的協力合作下，善用人工智慧視覺識別技術在海洋資源管理中的應用，重點關注綠蠵龜保育和通過結合公民科學和人工智慧協同的混合智慧（HI）框架，促進公民參與，希望達到教育遊客改變遊憩行為模式。在 AI 辨識綠蠵龜研究中，發現影像多樣化的小型訓練集，即可以訓練出高效能的 YOLOv5s 模型，提供未來運用 AI 調查野生動物的資料管理需求。三貂角混合智慧研究中，在 AI 的識別輔助下，不僅能促成公民科學參與者對科學數據的集體調查，且能利用機器學習結果來衡量與增進公民科學調查數據的品質，因而能評估調查協議策略的優缺點，且產生一個交互的、持續的、迭代增強混合智慧學習環境，在同時兼顧聯合國永續發展指標中的「良好工作與經濟發展」、

「負責任的消費與生產」與「維護海洋資源」，對於未來海洋保護區的設定和管理提供社會與科技（Socio-technology）綜合模式、確保在海岸生物多樣性資源保護的效能和永續經營。

關鍵字：綠蠵龜、三貂角、YOLO、公民科學、人工智慧、混合智慧、岩礁潮間帶生物多樣性、永續發展指標。

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Abstract

The utilization of littoral zone resources by human populations has evolved from traditional fisheries to a burgeoning blue economy paradigm, notably in coastal recreation. However, contemporary challenges such as population growth, urbanization, and climate change have precipitated notable ecological impacts on intertidal ecosystems, necessitating multifaceted approaches to ensure sustainable management. Studies in Little Liuqiu and Cape Santiago illustrate this dynamic, showcasing the tension between economic imperatives and environmental stewardship in the face of increasing tourist pressures. Despite legislative efforts, regulatory gaps persist, highlighting the importance of community-led conservation initiatives. This study aims to explore the integration of visual recognition AI technologies in marine resource management, focusing on green sea turtle conservation and citizen participation through a hybrid intelligence (HI) framework combining citizen science (CS) and AI-assisted learning methodologies. Through this experimentation, the streamlined YOLOv5s model consistently eclipsed its more complex counterparts in performance. The Santiago HI initiative not only streamlines

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the collective gathering and AI-assisted analysis of critical data but also utilizes machine-learning outputs to assess data quality, informing subsequent data collection and refinement strategies. This process fosters a mutual and continuous HI learning environment through collective and iterative enhancement. Our HI model plays a crucial role in promoting community engagement and public participation in CS efforts, developing the skills needed to document changes in rocky intertidal biodiversity. These efforts are essential for guiding the design and socio-technology governance of future Marine Protected Areas (MPAs), ensuring their effectiveness and sustainability in alignment with SDGs 8, 12, and 14 in marine conservation.

Keywords: Green Sea Turtle, Biodiversity, Conservation initiative, Citizen Science, Marine Protect Areas, Rocky Intertidal Ecosystem, Hybrid Intelligence, YOLO, SDGs.

中英文專有名詞與簡寫

英文	簡寫	中文名詞或解釋
Adaptive Survey Protocol	ASP	調適調查協議：由 PSP 根據實況修改後的調查規範。
Annotate	NA	標示: 對出現在影像中物件進行繪框與寫上類別名稱。
Bounding Box	NA	邊框：在標示物件時，所畫出的外圍框。
Citizen Science	CS	公民科學：具有科學意義的公民參與活動。
Class	NA	類別：欲由神經網所辨識出的種類
Confusion Matrix	NA	混淆矩陣：用於分辨 AI 模型對不同類別的分辨能力
Convolution Neural Network	CNN	卷積神經網路: 用以辨識圖形空間特徵的神經網路。
Hybrid Intelligence	HI	混合智慧：人機協力作用
Instance	NA	實例：影像中被標識出的物件
Intersection of Union	IoU	重疊率: 物件偵測所預期的樣框與實際標識的重疊區域。
mAP	mAP	平均精準度：預測出所有物件平均精準度
$mAP_{0.5}$	$mAP_{0.5}$	平均精準 $mAP_{0.5}$：在 IoU 重疊 50%以上的所有平均精準度
$mAP_{0.5:0.05:0.95}$	$mAP_{0.5:0.05:0.95}$	平均精準 $mAP_{0.5:0.05:0.95}$: 在 IoU 重疊 50%到 95%間 10 個閥值的所有平均精準度。
Neural Network	NN	神經模型
Object Detection	NA	物件偵測：從影像中偵測出不同的物件。
Precision	NA	精準度：預測物件的準確度
Proposed Survey Protocol	PSP	建議調查協議: 設計給公民科學計畫參與者的一致性調查規範。
Recall	NA	召回率：預測物件的出現率
Survey Protocol	NA	調查協議：參與者進行調查的科學方法

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第 1 章 緒論

1.1 人類世對海洋資源的衝擊

人類活動對地球的生態系統留下不可磨滅的痕跡，開啟了「人類世紀」(the Anthropocene epoch)(Waters and Turner, 2022)。人口增長和城市化的雙重壓力加重了對海岸地區的人為影響(Neuman et al., 2015)。此外，因氣候變化及其導致的嚴重風暴進一步加劇了岩礁潮間帶生態系統的衝擊影響(Donnelly et al., 2004)。當前，許多對海岸生態系統的利用已從傳統的漁業開發，轉變為以休閒活動為主，包括釣魚、冒險旅遊和環境教育等活動。因此，海岸管理需採取更廣泛、多重的策略，包括整合法律、經濟、休閒、教育、技術和媒體途徑等方式。這一策略不僅在改變人類直接危害的行為，更是呼籲社會廣泛參與產生約束力，共同保護生態環境。針對人類世紀設計的海岸管理策略，應該全面了解各種現況與困境，並考慮優先預防性行動，才能有效應對此世紀的各種不確定性。解決這些管理挑戰，往往需要跨學科合作、利益相關者的參與、調適性管理技巧、政策的協調整合、可持續的融資機制、增強抗壓能力的措施，以及強調技能開發和民

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眾教育的重要性（Rangel-Buitrago, 2023）。

沿海區域尤其是海岸潮間帶，因其豐富的生物多樣性而被譽為海洋生產力的樞紐（Lubchenco and Menge, 1978）。這些生態系統為高歧異性的海洋生物提供棲息地，且以多種直接或間接方式為人類社會帶來利益（Polunis et al., 2005）。例如，它們不僅是重要的食物來源，還提供經濟發展的途徑，增加休閒活動的多樣性，並有助於文化遺產的保護（Barbier et al., 2011; Worm et al., 2006）。城市附近的岩礁潮間帶系統，對生態平衡的維持，以及在經濟及社會活動中，扮演重要的關鍵角色（Barbier et al., 2011; Worm et al., 2006）。

都市附近的海岸岩礁地區對人群的吸引力，往往會考驗該區域的生態韌性，甚至反應其脆弱性。近年來，海岸旅遊的增長和相關的經濟利益（Stoeckl et al., 2010; Tapsuwan and Asafu-Adjaye, 2008）吸引了大量遊客造訪，人類的活動往往對當地生態環境造成壓力。住在擁擠空間的城市居民尤愛寧靜的海岸景觀（Ergin et al., 2006），並期待與海洋生物的近距離接觸，但隨意捕抓潮間帶海洋生物，甚至踐踏等活動，會對海洋生物棲息地造成負面壓力（Orams, 2002; Curtin, 2003;

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Velando and Munilla, 2011）。岩礁潮間帶地區充滿各式各樣的微棲息地，遊客的一些看似無害的行為，如在潮池內行走或好奇地翻動石頭等行為，會對生態造成長期的影響。群眾干擾甚至造成一連串的反應，如導致藻類種群減少，包括巨藻和珊瑚藻類型（Schiel and Taylor, 1999），進而對棘皮動物（Ghazanshahi et al., 1983）、軟體動物（Roy et al., 2003; Kido and Murray, 2003）和甲殼類動物（Murray et al., 1999）造成明顯的衝擊。

1.2 藍色經濟與永續目標

海洋或沿海旅遊被視為藍色經濟的一部分（World Bank, 2017），也符合促成島嶼永續發展的海洋管理政策（Bhattacharya and Dash, 2021）。欣賞海洋生物已成為全球旅遊現象，對地方經濟發展有明顯的貢獻（Scuderi et al., 2022）。例如，賞鯨活動每年產生約 300 萬美元的收入（Guidino et al., 2020），而加利福尼亞灣的基於自然觀察的海洋旅遊每年吸引約 896,000 名遊客，帶來 5.18 億美元的收入並直接支持 3,575 個工作崗位（Cisneros-Montemayor et al., 2020）。欣賞海洋生物雖亦造成海洋生態衝擊，但被認為比傳統的漁撈行更為永續，且能同時促進沿海

經濟發展，有管理性的藍色經濟預期可符合聯合國永續發展目標（SDGs）中的第 8 項（良好工作與經濟成長）、第 12 項（負責任消費與生產）與第 14 項（保育及維護海洋資源）等指標。

1.3 海洋公民科學

對於海洋研究人員和海洋資源管理者來說，監測海洋生物種群的時空變化模式是一項艱鉅的任務，然而，這些生態變化的監測資訊，是構成有效的海洋或沿海資源管理的條件。矛盾的是，海洋生物的難以捉摸和不可預測性反而成為生態旅遊的吸引力，激勵公民投入時間、資源和努力，尋找隱蔽、稀有或瀕危物種。一旦發現這些物種，旅客往往會開心地用手機拍照並分享到社交媒體上。這些大量發文的內容，包括圖片、短片、時間和 GPS 地理資料，可作為生態監測和管理的寶貴參考（Toivonen et al. 2015; Elqadi et al. 2017; Cranswick et al., 2022）。

海洋覆蓋了地球表面的絕大部分，擁有尚未被科學家和資源管理者探索的廣闊新領域。海洋公民科學（Marine Citizen Science, MSC）已成為填補海洋研究知

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識空白的關鍵手段。這種方法不僅增強了政府和社區的能力，而且還促進了全球保護海洋的努力。透過運用海洋公民科學的方式，全球海洋保護的參與和倡議顯著增加（Cigliano et al., 2015）。與傳統科學方法相比，公民科學的成本效益比（CP值）極高（Hyde et al., 2015），且在精心設計與運作下，已證明能產生嚴謹的數據和寶貴的發現，這些成果亦可顯著影響政策和決策過程（McKinley et al., 2017; Warner et al., 2017）。此外，海洋公民科學運動促成大眾的海洋科學素養，增強了參與者的學習（Turrini et al., 2018），並促進了海洋知識的廣泛傳播（Toivonen et al., 2015; Nursey-Bray et al., 2018）。參與海洋公民科學亦賦予社區能力，使他們與海洋環境建立深刻的聯繫，此參與為他們及其更廣泛的圈子提供了關於海洋問題的關鍵知識，範圍涵蓋從鯨豚保護（Cranswick et al., 2022; Matear et al., 2019）到海洋塑膠污染威脅（Zettler et al., 2017）以及海洋空間規劃（Jarvis et al., 2015）。當由社區驅動時，公民科學倡議亦可以將科學研究成果，無縫轉化為可行的政策和管理框架（Danielsen et al., 2010）。

邀請大眾參與科學數據的收集、分類或科學分析（Bonney et al., 2014）的公民科學，成為一種獨特的研究方法與趨勢。過去公民科學在多項海洋研究工作

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中發揮了重要作用。值得注意的計畫，包括監測礁魚生態系統（Pattengill-Semmens and Semmens, 2003）、追蹤皇后海螺種群（Cigliano et al., 2014）、識別海草床動態（Zhang et al., 2023）以及繪製海洋垃圾分佈模式（Chiu et al., 2020; Hidalgo-Ruza and Thiel, 2013）。公民科學在海洋項目中的獨特優勢在於其擴大研究的時空範圍的能力（Miller-Rushing et al., 2012; Roy et al., 2012; Ward et al., 2015）。然而，整合公民科學並非沒有挑戰。關注點通常集中在非專業人士收集的數據質量上，特別是對於複雜的生物多樣性數據集，對於數據的科學品質疑慮可能會妨礙它們的應用（Burgess et al., 2017）。儘管如此，最近的創新提供了解決方案。正如 Earp et al.（2022）在藻類潮間帶研究中所強調的，如果在嚴格的實施調查協議下與確保足夠的培訓，以及持續細膩地驗證數據，可以提升數據的質量，公民科學家收集的數據可以接近專業人士所獲得的藻類數據。

1.4 海岸資源保育

台灣對於海洋類瀕危物種的保育，例如綠蠵龜的法律保育，引用行之多年的野生動物保育法進行執法，嚴禁捕獵、騷擾、展示、買賣等違法行為（農委會）；

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在國際間則嚴格管制瀕危物種的國際貿易買賣（CITES）。對於廣泛的海岸或沿海，目前尚無海洋保護區特定的法源。所幸，海洋保育署（Ocean Conservation Administration, OCA）於 2019 年擬定海洋保育法，希望能符合海洋生態保護的管理需求。該法草案第七條將具有顯著生物多樣性的沿海地區，指定為需要特別保育管理的海洋保護區（Marine Protect Area, MPA），且該草案第六條要求實施包括生態調查在內的各種管理措施。海洋保育署在 2020 年採取先期的生物多樣性生態調查，在台灣本島及其周邊島嶼的 67 個岩礁進行生物多樣性與環境評估。他們利用穿越線和樣框方法，來評估海洋物種的豐富度、生物量，以及包括污水排放口、人造設施、旅遊活動、泥沙淤積和潮池的豐富度等環境因素。通過整合生物多樣性和環境指標，決定此 67 個岩礁的保育優先順序。在調查地點中，其中四個地點位於三貂角，即為馬崗海蝕平臺、萊萊-1、萊萊-2 和萊萊-3。值得注意的是，調查報告結果顯示位於三貂角東南邊緣的萊萊-2 調查點，具有最高的海洋物種多樣性，且與鄰近的萊萊-3 地點，同時被列入具有最高保育價值的岩礁點（海洋保育署，2021）。

1.5 人工智慧應用在海洋保育

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人工智慧（AI）是一種機器學習演算法，通過數據資料集（dataset）進行學習。一般而言，學習類型分為監督學習和非監督學習，無論哪種類型，機器學習都需要通過人類收集的數據（監督學習）或由感應機器設備驅動的數據流或是大量的資料來源進行分析（非監督學習）來訓練神經網路（陳，2023）。人工智慧技術的應用已迅速普及於我們的日常生活中，並極具潛力對公民科學或社區賦能，尤其對於廣闊的海洋保育有極大的潛力。即使如此，當前在人工智慧的實際應用中，尚不能完全由 AI 獨立解決問題（Dellermann et al. 2021）。

人工智慧模型的成功應用不僅依賴於高效的神經模型本身，還依賴於高品質的圖像資料庫（Own-Bar and Trivedi, 2017; Wei et al., 2018）。儘管預訓練的神經模型如生成式 GAI，可以協助轉移和縮短學習過程，但仍然需要為新的任務訂制特定資料集（Ozbulak et al., 2016; Windrim et al., 2016）。為了在生態中偵測出海洋生物，訓練資料集必須涵蓋各種海洋生物特徵，包括在背景偽裝下、環境條件的快速變化（如波浪和光線）下，以及圖像中背景中存在的各種雜訊（如波紋、亮度和色度等）。因此，在多樣化的環境中收集適合的海洋生物圖像資料集，對

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於是否能有效訓練出高效率的 AI 模型非常重要。

1.6 研究動機與目的

新北市三貂角文化發展協會為減緩遊客日益增加的壓力，主張將漁港西側的海蝕平臺，設立為海洋保護區，當設定保護區後才能有法源可循，管理減緩對環境有害的行為，而海岸的生物多樣性的科學評估，將會成為是否符合成立海洋保護區的關鍵因素（海洋事務委員會，2023）。社區成員基本上達成保育共識，初期先組織動員志願者進行沿海生物多樣性的公民科學調查。在為立法機構提供將此區域納入海洋保護區所需的科學數據之前，同時積極教育遊客關於沿海生態系統的知識，倡議教育遊客認識海洋保護的重要性，阻止可能傷害海洋生物和生態環境的活動，例如拋棄垃圾與營火等行為。

近年來，AI 影像辨識應用於海洋資源管理上方興未艾，然而，應用 AI 在海洋生物族群的變化研究還很有限。2020 年，Badawy 等人從 Google 和 ImageNet（Deng et al., 2009）收集圖像，創建了一個海龜數據集，並訓練了一個 Faster

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R-CNN 的神經模型（Ren et al., 2016），用在辨識海灘上的海龜。其所訓練出的模型表現在 IOU 0.8 的閾值下達到 95.7％的精準度。Álvarez-Ellacuría 等人（2020）也使用機器視覺模型 Mask R-CNN（He et al., 2017），來檢測漁市場中歐洲無鬚鱈 (Hake, *Merluccius merluccius*) 漁獲長度，推演該魚種族群在海洋中的動態，以實現資源的永續管理。此外，許多研究人員包括 Malde 等人（2019），French 等人（2020），Tseng 等人（2020），以及 Rick van Essen 等人（2021），將各種 AI 模型應用於自動辨識或分類不同種漁獲或拋棄的無經濟魚種。

收集海中活魚或海洋生物的水下圖像，與在船上或市場中的漁獲或卸貨環境不同。由於活魚或其他海洋生物，在與海床或海水背景融合的偽裝顏色特徵，而產生辨識的困難性。此外，海洋環境的光線變化多端，導致水下圖像的雜訊、亮度、色度、解析度和對比度等都可能發生變化，這些因素使得難以蒐集到足夠圖像資料集來訓練模型。大規模用於 AI 模型辨識研究的海洋生物圖像數據集才正在積累中，2022 年，Muksit 等人（2022）檢查了來自 20 個不同真實世界的海岸環境（如岩礁、紅樹林、巨石、礁溝、岩架、海草床等）的魚類圖像，這些圖像來自大規模數據集 Deepfish（Saleh et al. 2020）和 OzFish（Australian Institute of

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Marine Science, 2020）。辨識海洋生物需要運用深度學習算法驅動，更需要大量標示的訓練資料集才能實現高精度的模型（Malde et al., 2020; Beyan and Browman, 2020）。這往往需要海洋生態學家的領域知識和與資訊科學家的跨學科合作，以收集和反覆修訂具有代表性的數據集（Weinstein, 2018; Schneider et al., 2019; Goodwin et al., 2022）。

由於蒐集野生海洋生物圖像不容易，本論文先以研究辨識小琉球的綠蠵龜的 AI 為目標，由筆者在小琉球的生態旅遊經營者協助下，蒐集綠蠵龜的各種情境下的圖像，探討以何種綠蠵龜圖像資料集的數量與品質，與不同的 AI 神經模型匹配，方能訓練出最高辨識能力的神經模型，且設計程式部署訓練後的 AI，讓前往小琉球觀賞綠蠵龜的業者與遊客使用。

除了提供遊客或生態導遊使用，人工智慧逐漸被用來增強個人與社區對環境的監測與認識（Hsu et al., 2022）。儘管公民科學和人工智慧通常被視為生態監測的獨立工具，然而最近的研究顯示，人類智慧和人工智慧之間的協力關係，稱之為混合智慧（HI）（Dellermann et al., 2021; Rafner et al., 2021），得以產出有更好

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的效果。本文進一步研究透過公民科學計畫的大眾參與效益，與人工智慧複雜的分析能力相結合，以期在公共議題和科學議題上，促進多方參與者達成更大的共識行動（Lotfian et al., 2021）。甚且，適當的整合可以加速傳統科學方法的資料收集和處理，這也暗示可有效協助生態監測和保育的各項行動（McClure et al., 2020）。

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第 2 章 用於永續生態旅遊之綠蠵龜圖像 AI 模型之生成訓練與效能評估

2.1 前言

從過往紀錄來看，全球海龜族群數量的減少，與其肉、蛋和龜殼的捕獲有關（Chaloupka et al., 2008）。然而，最近的研究發現情況變得更加複雜。氣候變遷（Heppell et al., 2022）與棲息地污染（Sposato et al., 2021 ）等因素會影響海龜性別決定，加上其餘各種人為壓力等因素也導致了全球海龜數量的減少。為此，海洋保護區 (MPA) 和海洋國家公園已成為海龜重要的保護措施。這些區域將人為干擾降至最低，為綠蠵龜提供覓食、繁殖和築巢的安全棲息地，從而能對瀕臨絕種的物種進行有效的保育工作。綠蠵龜及其產製品的國際貿易受《瀕危野生動植物種國際貿易公約》(CITES) 管制，凸顯了全球對其保護的一致性。作為西半球綠蠵龜的重要繁殖地，哥斯達黎加的托爾圖蓋羅國家公園（Tortuguero National Park）海洋保護區內設定特別分區，例如海洋國家公園的「B」區，強制執行「只看不拿」的政策，禁止採集（Day, 2002）。在繁殖季節時，嚴格控制人類活動和

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照明，並全面禁止捕撈或騷擾海龜（Gutiérrez-Lince et al., 2021）。同樣，在台灣，《野生動物保育法》嚴格禁止任何騷擾、捕獲、採集或交易海龜及其產製品。

根據 Weaver 和 Lawton（2007）的研究，生態旅遊是一種基於自然的旅遊，有利於保護工作和當地居民的福祉，也是補償因野生動物保育造成的當地社區經濟限制的一種方法。Pegas et al.（2013）回顧海龜生態旅遊的運作案例，並總結了鼓勵當地社區一起合作和參與的重要性。這種在地的合作方式除了改變傳統資源的利用方式，可減少對自然資源的消耗，並增加群眾對保育的支持。海龜生態旅遊的成功往往取決於遊客的現場體驗，其中包括環境教育和觀賞海龜（Tisdell and Wilson, 2005；Lamb, 2019），遊客透過 Instagram 和 Facebook 等社群媒體線上分享與海龜的接觸體驗，能有效促進夏威夷拉尼亞凱亞海灘（Laniākea Beach）的海龜旅遊業。因此，能準確估計海龜的出現和現場觀賞體驗，對促進永續生態旅遊非常有幫助。

台灣西南部的小琉球，傳統上是依賴漁業維生的島嶼，由於漁業資源逐漸枯竭，該島的經濟漸漸轉向生態旅遊，特別是吸引到觀賞綠蠵龜感興趣的外來遊客。

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適當的保育措施與Covid-19疫情期間的封島行動，使得該地區綠蠵龜族群數量大幅增加。估計2019年在該島海岸線上紀錄到199隻野生海龜，到了2021年，增加到805隻（OCA, 2021）。儘管如此，隨著2022年Covid-19限制的解禁，該島的旅遊業激增，遊客人數增加了一倍多，從疫情期間的173,307人增加到362,660人（琉球鄉辦公室，2023）。遊客的湧入不僅帶來了經濟收入，也引發了對野生動物騷擾相關的法律案件，造成危害綠蠵龜的隱憂（海巡署局長辦公室臉書， 2022年3月8日檢索）。為了解決這些問題，當地社區和管理當局實施了包括保育教育、生態旅遊宣傳與執法等管理措施，以防止綠蠵龜受到騷擾。

在當地社區的期望下，人工智慧如何使小琉球島的旅遊業和綠蠵龜保育同時可受益？在本研究中，開發一種可以辨識出在自然棲息地的綠蠵龜的人工智慧服務，從而豐富遊客的觀賞體驗並提高他們的保育意識。本研究探索最佳的訓練資料集、最優化的人工智慧模型、有效的評估模型和實際部署使用，以促進綠蠵龜資源的永續管理。

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2.2 材料與方法

2.2.1 調查地點與影像資料蒐集

距離台灣本島西南海岸約 15 公里遠的小琉球，為面積 6.2 平方公里的珊瑚礁島。長約 12 公里的海岸線，由珊瑚礁、岩礁、沙灘與 4 個漁港所組成。根據海洋保育署的報告，整個海岸海域都有綠蠵龜出沒的蹤影，其中出現頻率最高處，主要在花瓶岩海岸（北）、肚仔坪（西北）、杉福漁港（西）和龍蝦洞（東）等 4 個區域（野澤等，2019）（Fig. 1）。

本研究從 2016 至 2021 年期間，在與當地生態旅遊業者合作協助下，主要在上述 4 個地點進行野外綠蠵龜拍照蒐集資料，工具包括使用無人機 (Dji Mavic Pro M1P)、水下相機 (Olympus TG-3)、手機等攝影設備，進行野生綠蠵龜調查與拍攝調查。在 2019 年以前，影像蒐集緩慢，之後則更容易發現綠蠵龜的出沒，最後整理出在空拍、岸邊與水下各種情境下的影像 781 張。此外，後續又從臉書「海龜點點名」網站整理出 681 張圖像。

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2.2.2 AI 模型選擇與訓練方方法

Fukushima 於 1980 提出影像辨識的開創性深度學習演算法—卷積神經網路（CNN)。此演算法通常用於辨識出單一物件的圖像，稱之為圖像分類（陳, 2023)。之後，Girshick 等人（2014）設計出在影像中分辨不同物件的神經網路模型（R-CNN)，該模型演算時先將影像分割成大約 2,000 個小區域，然後採用卷積網路演算法，依序從每個小區域中提取不同物件的特徵。以此為基礎，又演化出「你只看一眼」（You Only Look Once , YOLO）模型演算法，該模型雖將輸入的圖像劃分為更少的區域（例如，7x7 像素），YOLO 運用空間上不同的邊框（Bounding Box）結合分類機率，將物件偵測重新定義為迴歸問題（Redmon 等人，2016)。這種演算法允許 YOLO 從輸入的影像直接計算預測邊界框和類別機率，從而簡化運算的過程。當 YOLO 演進到第 3 版本，YOLOv3 引入了一種具有3種網格大小的平行運算架構，有助於識別不同距離與大小的物體，從遠到近、從出現在小型到大型的物件影像（Redmon and Farhadi, 2018；Guerrieri and Parla, 2021)（Fig. 2)。在本文研究中，將比較 YOLOv3 模型與較新的 YOLOv5 模型

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差異，YOLOv5 包括大小兩個版本，v5s 為緊湊架構設計的縮小模型，v5l 則為較大架構，3 種模型用於辨識野生綠蠵龜。YOLOv3, YOLOv5s 和 YOLOv5l 的程式開放碼都可在 GitHub 上獲取。我們使用 Linux 桌上型電腦，圖形處理卡 RTX3090-24G GPU 提供神經模型運算資源，訓練模型時超參數（hypermeters）設定為：預訓練權重、訓練批量為 32、影像大小 800x800pixel、學習週期 (epoch) 為 200 回。訓練前，所有影像裡的綠蠵龜，都使用 labellmg 程式進行標記，代碼為類別（c）、座標位置（x，y）和面積大小（寬度 w，高度 y）（Fig. 2），而所有訓練資料被隨機分割為訓練集（80%）和驗證資料集（20%）（Fig. 3）。

2.2.3 AI 模型效能評估

AI 辨識物件的結果共有 4 種情況：1）成功辨識出實際對象－真陽性（TP）；2）成功辨識非實際對象－真陰性（TN）；3）未能辨識實際對象－偽陰性或漏報（FN）；4）將非實際對象錯誤地辨識為實際對象-偽陽性或誤報（FP）。計算模型的精準度 precision 如公式 (1)，計算召回率 recall (2)，計算 F1-score（精準度和召回率的平均值）(3)。IoU 為計算預測邊框 Bp 中與實際真值邊框 Bgt 的面積

重疊的比率(4)，如以下公式所示：

$$precision = \frac{TP}{TP+FP} \qquad (1)$$

$$recall = \frac{TP}{TP+FN} \qquad (2)$$

$$\mathrm{F1-score} = 2\times\frac{precision\times recall}{prescision+recall} \qquad (3)$$

$$IOU = \frac{aera\ |Bp\ \cap Bgt|}{aera\ |Bp\ \cup Bgt|} \qquad (4)$$

公式 mAP $_{0.5}$(5) 量測當 IoU 為區域重疊閾值 50%以上時所有情況精準度的平均值。

$$mAP_{0.5} = \frac{1}{n}\sum_{i=1}^{n} AP_{category\ i} \quad when\ IoU\_threshold = 0.5 \qquad (5)$$

而公式 mAP $_{0.5:0.05:0.95}$(6) 表示當 IoU 值 0.5 到 0.95（以 0.05 為增量）之間 10 個閾值狀況下精準度的平均值。

$$mAP_{0.5:0.05:0.95} = \frac{1}{10}\sum_{i\in[0.5:0.05:0.95]} AP_i \quad when\ IoU_{threshold} = 0.5\ to\ 0.95 \quad (6)$$

2.2.4 AI 模型最佳化實驗

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在本研究中，為綠蠵龜管理系統確定最有效的人工智慧模型，實驗評估訓練資料集的大小和組成，如何影響不同 YOLO 模型的辨識表現，包括以下三種組合實驗：

(a) 訓練資料量實驗

使用不同數量的兩個資料集（單類別 class）訓練 YOLOv3、YOLOv5s 和 YOLOv5l 模型，然後根據精準度、召回率和 F1 得分進行評估。第 1 個訓練資料集包括研究期間收集的 781 個圖像, 而第 2 個資料集包括前面資料集加上 681 個額外圖像，總數達到 1,462 個影像。

(b) 資料類別分類（class）和實例（instance）量影響實驗

透過將訓練資料集影像中的物件（object）或實例（instance）標示（annotate）為單 1 個類別 (class)，研究資料分類和實例數量對識別效能的影響。然後使用相同的設定下, 將相同的資料集影像重新標示為 2 個和 3 個類別，以了解標示的數量和品質如何影響物件精準度 $mAP_{0.5}$。評估不同類別設定下每個類別的精準度，並在模型之間進行比較。

(c) 各種 YOLO 模型的整體辨識性能評估實驗

綜合上述實驗，總和評估 YOLOv3、v5s 和 v5l 在辨識綠蠵龜測試資料

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集時，各項辨識實驗的表現指標，包括 F1（精準度和召回率之間的調和平均值）、目標偵測的平均精準度（$\mathrm{mAP}_{0.5}$ 和 $\mathrm{mAP}_{0.5:0.05:\ 0.95}$）。

2.2.5 網路部署人工智慧模型提供辨識服務

當人工智慧模型訓練完成後，撰寫 Python-flask 網頁程式將之部署在可公開存取的伺服器上，公開給任何使用者透過網路綠蠵龜的辨識服務，同時方便使用者與 AI 服務系統的互動。

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2.3 結果

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2.3.1 蒐集資料的標示結果

Witherington 和 Witherington (2015) 在大西洋和墨西哥灣綠蠵龜族群的研究中，觀察到龜背甲的顏色與花紋與年齡有特殊關係。幼年龜（3-10 歲）和亞成龜（10-30 歲）往往在背盾片上呈現出鮮紅色的輻射條紋（Fig. 4a），而性成熟的龜（30 歲以上）則呈現出如黑褐色雜亂的大理石紋路（Fig. 4b）。同樣在本研究觀察中，在小琉球周圍出沒的綠蠵龜背甲殼上亦觀察到這兩種獨特的圖案。一種模式是“淺至深棕色陰影，帶有深色斑點”，因為此特徵通常在成年動物（> 30 歲）發現，將其歸類為大理石「GT/年長者」（Fig. 4b）。另一種模式是「帶有棕紅色放射狀的紅色」（Fig. 5a），將其歸類為「redGT/年青者」。進一步觀察到，大多數具有紅色放射狀圖案的動物體型較小，背後甲殼緣突出，此兩項花紋也都是青少年龜（<30 歲）的特徵。然而在以下情況，許多背甲圖案不容易識別：1）當從無人機上觀察影像時，遙遠且小的物件（Fig. 4c），2）當從海上觀察時，它們似乎與水面融為一體（Fig. 4d），和 3）當圖案從底下背光時變得不可見，或是

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只有動物的身體部位可見（Fig. 4e）。從 2 個資料集中，分別註記 1, 2, 3 種類別的 3 種情況，以作為後續實驗所用（Table 1）。

2.3.2 資料集數量對不同模型效應

在綠蠵龜辨識的單一分類的實驗中，評估 YOLOv3、YOLOv5s 和 YOLOv5l 三種模型的辨識性能。使用 781 個圖像的較小資料集和 1,462 個圖像的較大資料集，兩個訓練與測試集測試模型。用精準度、召回率和 F1 辨識指標來衡量成效。結果顯示，在使用較小資料集的情況下，YOLOv3 呈現出所有三個指標上都優於其它模型。YOLOv5s 在精準度和 F1 方面也都表現出優異的結果，而當在較小的資料集上訓練時，YOLOv5l 在所有三個指標都落後其他模型（Table 2）。

2.3.3 資料集標示方式對不同模型效應

此實驗將單一資料集分類為 1 到 3 個類別來評估模型的效能，隨後分析在同一類別設定中，增加實例量的影響。測試標示的配置設定是否可影響不同神經模

型對物件的偵測能力。結果顯示，僅 YOLOv5l 的實例（instance）量增加時與平均準確度 mAP$_{0.5}$之間存在穩定的正相關性，而在其他兩個模型 v3 與 V5s 則表現出不一致相關的變化。當類別“GreenTurtle_1”的實例數量從 685 個增加到 1287 個實例，與“MarbleGT/elder_2”的實例數量從 212 個增加到 609 個實例，此 2 種類別的平均 mAP$_{0.5}$表現在 YOLO5l 模型表現中呈現一致性增加。然而，在 2 個和 3 個類別中，當增加實例量反而可能會對 YOLOv3 和 YOLOv5 的平均準確 mAP$_{0.5}$產生負相關的影響，例如在“redGT/young_2”、“redGT/young_3”與“marbleGT/elder_3”3 種類別（Table 3）。

2.3.4 YOLO 模型性能綜合比較分析

在各項實驗分析中，3 個模型的 F1（Fig. 5b）、mAP$_{0.5}$（Fig. 5c）和 mAP$_{0.5:0.05:0.95}$（Fig. 5d）3 種驗證效能指標，基本上與實例數量呈現正相關。比較三個模型的 F1，YOLOv3 和 YOLOv5 在較少 685 訓練實例量的表現，卻優於 1,287 較多實例量（Fig. 5a），但這種反轉現象並未發生在 YOLOv5l 上（Fig. 5b）。且在所有情景下，YOLOv3 和 YOLOv5s 的 F1 均高於 YOLOv5l。在比較 mAP$_{0.5}$時，3 個

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模型的表現非常接近（Fig. 5c）。比較 $\text{mAP}_{0.5:0.05:0.95}$ 表現，YOLOv3 和 YOLOv5s 均勝過 YOLOv5l，但如比較 YOLOv3 和 YOLOv5s 則無法判斷哪個更好（Fig. 5d）。當合併實驗中所有效能指標結果，在綜合檢測（Boxplot）下，YOLOv5s 為表現最佳的模型（Fig.6）。

2.3.5 部署應用

為了促成遊客「只看不摸」禁止觸摸或騷擾綠蠵龜的行為，將實驗後最佳模型部署在雲端，提供大眾 AI 綠蠵龜辨識的服務。在網上部署使用 1,462 張圖片、2 類別的數據集訓練的 YOLOv5s，為遊客提供紅色/幼年或大理石色/成年綠蠵龜服務。當地導遊可以利用這項獨特且引人注目的 AI 技術吸引遊客參與，並引導遊客在前往島嶼海岸線的旅程中，尋找不同年紀的綠蠵龜。使用者由手機或行動裝備，可透過特別設計的用戶界面（UI）（Fig. 7a），然後上傳他們的圖像/照片到伺服器進行識別（Fig. 7b）。上傳的綠蠵龜圖像可以是來自空中無人機（UAV）調查、遊客在海岸線或漁港散步時的水面圖像，或是潛水員或浮潛者遇到游泳或休息的綠蠵龜的水下影像，辨識的結果將直接回傳給使用者（Fig. 7c）。

2.4 討論

2.4.1 訓練資料集數量與品質的影響

YOLO 是一種深度學習的演算法，其辨識表現不單只靠神經網絡架構改進，也靠訓練資料集的內涵。先前許多自動化海洋生物辨識 AI 的研究，側重於神經模型的改進，較少考慮到訓練資料集質與量的影響（Salman et al., 2020；Zhao et al., 2021；Muksit et al., 2022）。在本研究初始研究訓練綠蠵龜 AI 時，對訓練所需的圖像數量並無太多前人研究可依循，因此假設訓練的圖像數量越多越好。經過三年的實地採集後，方整理出了 781 張可能適合 AI 訓練的圖像。後來，從社群媒體平台《海龜點點名》增加 682 張圖像，增加了近 47％圖像。然而這些新增圖片使 YOLOv5l 模型的三個性能指標（精準度、召回率和 F1 分數）只提升了約 1%，亦只提高 YOLOv5s 的召回率，然而增加數量對於 YOLOv3 則整體性能反而造成下降（Table 1）。本研究顯示對於單一類別的標示，超過 700 張的訓練圖像，即可讓 YOLOv3 和 YOLOv5s 的精準度和召回率達到 97%以上的令人滿意結果。據本文在撰寫以前，有關海龜圖像 AI 辨識，僅由 Badawy and Direkoglu

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(2020)完成，他們從網路資料庫取約500張海龜照片來訓練Faster R-CNN模型，可達到95.7%的精準度，但其文章中所展現的圖像僅是出現在沙灘上的影像。

如果與其他海洋生物辨識研究相比，Salman等人(2020)利用了龐大的OzFish資料庫(Australian Institute of Marine Science, 2020)，包含1,800張圖像和43k個實例，取得了72%的F1分數。當將YOLOv3應用於他們自己的DeepFish資料集時（包含4,505張圖像和15k個實例），其F1分數達到了94%。相較之下，我們的研究使用了包含1,462張圖像和1,608個實例的資料集，YOLOv3能達到97.19%的F1分數（Table 1）。即使用包含781張圖像和856個實例的較小資料集，我們也獲得了97.96%的F1分數。這些結果顯示，模型的表現效能不僅受到資料數量的影響，也可能受到資料集影像的品質和內容影響。

為研究資料集實例數量的影響，我們進行不同類別組成的實驗。整體趨勢顯示，每個類別的檢測精準度（以mAP$_{0.5}$表示）與其實例數量呈正相關，尤其對於YOLOv5l模型，表現出一致性的正相關。然而，對其他兩個模型v3與v5s卻未觀察到此種趨勢。在3種類別設定中，GreenTurtle_3類的mAP$_{0.5}$明顯高於

其他兩類，儘管該類的實例數僅有 221 個（Table 3）。這種差異可能源於該類別的影像存在不同範圍的物體大小，從大物體（例如身體部位的特寫視圖）到小物體（例如無人機拍攝的空中照片）（ Fig. 4c, d, e）。因此可推論出，當與只有統一物件面積大小的資料集相比，具有各種物件面積大小的資料集，似乎可以顯著提高平均精準度 $mAP_{0.5}$。這種情況可以與 YOLOv3 模型及其後續變體的設計理念相關聯，與主要識別 2D 平面圖案的 R-CNN（Girshick, 2015）不同，因 YOLOv3 及其後續改善模型版本，加入可演算辨識出物體在遠、中、近 3D 空間距離，所產生的面積大小不同（Fig. 2）（Redmon and Farhadi, 2018）。

2.4.2 不同 YOLO 版本性能比較

YOLO 演算法以動態發展的開放架構，歡迎任何人修改架構，以持續增強其性能。往往利用 MS COCO 數據集（Lin, 2014）訓練測試比較 YOLO 各個版本的優劣。理論上，後續開發成功的版本，在速度和精準度各方面應該均優於其前身（Jiang et al., 2022；Wang et al., 2022）。因此，YOLOv5l 和 YOLOv5s 在精準度上理應超越舊的 YOLOv3。而 YOLOv5s 是 YOLOv5 模型的簡化版本，以犧牲

一定的精準度為代價來優化速度，好用在適應運算能力有限的邊緣設備（edge computing）或用在監測器的即時運算。相對而言，YOLOv5l 作為 YOLOv5 模型的大型版本，具有更多的神經運算元，但需要更多的運算資源，應該能夠提供更卓越的精準度。然而，本研究實驗結果出人意料地顯示，YOLOv3 在準確性方面實際上超越了 YOLOv5l。值得注意的是，儘管 YOLOv5s 的設計較為精簡，在應用小規模訓練資料集時，與 YOLOv5l 更複雜多層運算架構設計相比，反而表現出更卓越的性能。也儘管在 MS COCO 數據集上的檢測效能排名為 YOLOv5l > YOLOv5s > YOLOv3，本研究得出的排名卻為 YOLOv5s > YOLOv3 > YOLOv5l（Fig. 6)。模型性能的差異也可能源於訓練資料集內容的差異，MS COCO 資料集來自一般日常生活影像，是一個廣泛日常物件影像的集合，其中包含 330,000 張影像和 1,500,000 個實例巨大的資料量。相較之下，本研究的訓練資料集則是專門來自小琉球島野生綠蠵龜的目擊影像。Mahmood 等人（2020）研究隱蔽性的龍蝦辨識，嘗試為 YOLOv3 模型補充適量的合成影像（例如 100、250 或 500 張圖像)，確實可以提高 $mAP_{0.5}$ 值，但過多的合成影像（例如 500 個）則可能導致 $mAP_{0.5}$ 值降低。此研究與本研究反應出同樣的趨勢，顯示在較少數量的資料集訓練時，YOLOv3 和 YOLOv5 都產生優異的 F1 分數（Table 1）和 $mAP_{0.5}$ 效

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能（Table 3）。

另外，基於我們的兩個訓練資料集所訓練的模型，訓練後獲得的權重分別為 YOLOv5s：14.8 MB、YOLOv5l：93.6 MB 和 YOLOv3：246.3 MB。較小的權重意味著較少的運算參數，在運算過程中硬體和能源需求也較少，在考量平衡性能、精準性和運算效率，本研究選擇 YOLOv5s 部署在線上服務。

2.4.3 AI 服務與使用者體驗

能在野外目睹綠蠵龜的即時資訊，對經營生態旅遊的業者和進行環境教育的教師而言，扮演重要角色。而使用人工智慧的即時服務，可增加遊客或學生探索體驗，遊客或學生可利用智慧型手機拍攝出沒海岸的綠蠵龜影像後，上傳網路，經過 OLOv5s 模型，辨識精準度分別為 96.2%和 93.1%平均精準 $mAP_{0.5}$，分辨出年輕紅色樣貌和年長大理石樣貌的綠蠵龜不同類型綠蠵龜，結果隨即回傳給使用者（Fig. 7）。這種即時的現場辨識，不僅豐富首訪者和初次使用者的體驗，使得在自然環境中的海龜邂逅變得更加難忘。旅遊經營者亦可利用這種 AI 服務設計

環境教育和旅遊行程，鼓勵遊客積極參與觀察綠蠵龜群落。遊客拍攝到野生、自由漫遊的綠蠵龜後，經過人工智慧系統識別和註釋的綠蠵龜照片，可在個人社交媒體平台上分享。共享的體驗不僅豐富旅行記錄，也支持了綠蠵龜生態旅遊的推廣（Lamb, 2019）。在這一辨識過程中，遊客的行為自然受到制約，避免驚擾或干擾到綠蠵龜，能促進環境保育教育的目標，同時減輕野生動物保護執法的壓力。

2.4.4 使用者與 AI 互動

通常用於海洋環境中監測漁獲量，或運送魚貨的 AI 辨識自動化系統，往往以固定攝影機獲取影像。在這種在固定攝影距離人為環境下，相對而言較容易將人工智慧模型表現與人類量測結果進行比較，或是經由人工校正補足人工智慧在計量上的缺失（van Helmond et al., 2017; Álvarez-Ellacuría et al., 2020; van Essen et al., 2021）。然而，本研究的 AI 服務對民眾開放時，在各種應用的情境與使用者不明的情況下，很難將 AI 的精準度與人類量測進行比較。儘管如此，我們仍能追踪到伺服器端的使用者輸出入差異。本研究的系統有時會錯將使用者提交的卡

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通和壁畫作品識別為真正的綠蠵龜（Fig. 7d），這種錯誤輸出被稱為「人工智慧幻覺」(Hallucination)，即系統產生的真實但不正確或虛構的結果（Goodfellow et al., 2015）。此外，某些使用者故意上傳非自然圖像，藉此挑戰人工智慧的識別能力，也顯示出他們對人工智慧辨識潛力的興趣。從使用者體驗的角度來看，能夠辨識出類似於海龜的實體，即使是錯誤的，也比無回應的系統更好。重要的是，使用者所提交的各種情境下圖像，未來經過標示後，將成為 AI 模型訓練和精準度改善的寶貴資源。此外，這些提交的圖像內容亦將提供進一步了解人與綠蠵龜互動的資料庫，包括拍照的時間和 GPS 座標等詳細信息，這些資料具有透露綠蠵龜族群的時空分佈模式的潛力，值得進一步探索和研究。

2.4.5 AI 辨識對綠蠵龜保育的影響

在整合人工智慧深度學習的即時影像辨識 YOLOv5s 模型，是否能對海洋保育工作產生有意義的影響。透過利用這項技術，有潛力能將遊客從被動觀察者轉變為積極的保育參與者，對保育的影響會是下列三重的：

（1）教育影響：人工智慧服務讓使用者能識別和了解綠蠵龜在自然棲息地出

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沒模式。這種互動體驗不僅可以進行環境教育，還可提高人們的保育意識，從而加深對海洋生物的認識，積極參與者更有可能支持並積極為保育措施做出貢獻。

(2) 行為改變：本研究提倡以非侵入性的方式與海洋生物互動，希望遏止不當行為，例如觸摸或追逐綠蠵龜行為，所帶來綠蠵龜壓力和傷害。也透過業者和教育者鼓勵更負責任的生態旅遊行為，減少對海洋野生動物的負面影響。

(3) 資料收集和監控：遊客拍攝的照片有雙重目的：增強遊客體驗並為綠蠵龜目擊時的寶貴資料庫做出貢獻。這種眾包方法（outsourcing）有助於監測海龜族群的健康和分佈，為自然資源保護者和研究人員提供重要的線索。

總之，以這種方式利用先進技術不僅豐富遊客的體驗，且在出現更、廣泛的海洋物種保護領域中也能發揮出重要的作用。

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第 3 章 應用人機協同於海洋保護區倡議

3.1 前言

鄰近台北新北大都會區約 50 公里的三貂角，位處台灣島最東端黑潮與沿岸流的交會處。400 年前由西班牙探險家命名，其 4.86 公里的海岸線以海蝕平台和岩礁海岸著名，整個三貂角區域只有一小型馬崗漁港社區。隨著漁業資源的減少，年輕人紛紛湧入城市，政府為了促進旅遊業，於 2011 年修建了一條沿著海岸的自行車路線，成功地吸引大量遊客造訪，但也引發了當地住民對其海岸生態的擔憂。當地為了保護漁村文化和海岸生態系統，成立「新北市三貂角文化發展協會」（SDCDA）。目前三貂角海岸在法律保護上，只有依據《新北市都市計畫法》規定的「海洋資源保護區」（海保署，2019），設定限制劃設區域內的建設發展，但並沒有法令條文處理人為對海岸生態環境的不當行為。

三貂角海蝕平台上充滿凹坑 (pits)、凹槽 (grooves)、裂縫 (crevices)、岩塊 (rocks) 等各種地質型態，大的海蝕平台裂縫形成岩池（rock pool）或潮池

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（intertidal pool），岩層或岩塊地質結構性的複雜性，影響到當地海洋的生物多樣性（陳，2011）。同地區地質結構越複雜形成的微棲息地越多，如果沒有上述這些複雜岩礁微細結構，則其生物多樣性較低（Loke and Todd, 2016）。除了岩塊上固著性類群（sessile taxa）海洋生物如藻類、海綿、海鞘、藤壺、牡蠣等，移動性類群（mobile taxa）的海洋生物亦是潮間帶重要的生物多樣性來源。Davidson *et al*. (2014) 調查岩岸潮間帶高潮位、中潮位、低潮位地理空間，生物多樣性的歧異度（richness）與個體豐度（abundance），發現就在歧異度上而言，移動性類群的物種數量大約是固著性類群的 2 倍，但是在個體豐度上，固著性類群個體數量大約是移動性類群的 12 倍。可以預想的是，三貂角周圍的海蝕平臺的海洋生物多樣性，會根據地質結構不同而有空間（spatial）差異，且會隨著季風、潮流、水溫、日曬等氣候因素影響，其生物多樣性也會隨著時間（temporal）而變異。

本研究將運用 AI 辨識海洋生物技術，協同當地社區公民科學調查與教育的努力，為三貂角岩礁生態系倡議設立海洋生態保護區，並希望達到下列管理目標：

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1). 為三貂角岩礁生態系統建立一個時間與空間的生物多樣性資料庫。

2). 評估人工智慧模型的表現、公民科學的數據貢獻以及的兩者協同的影響。

3). 設計結合公民科學和人工智慧的混合智慧（Hybrid Intelligence, HI）框架，以持續進行生態監測和環境教育，以作爲未來倡議設立海洋保護區做準備。

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3.2 材料與方法

3.2.1 研究區域與公民科學調查計畫

研究區域位於三貂角海岸線的西北側，稱為馬崗海蝕平臺。此海蝕平臺（Wave Cut Bench, WCB）大小約為 160m 長與 70 m 寬（Fig. 8)。公民計畫的參與者由三貂角文化發展協會招募，接受 16 小時的海洋教育培力課程，由本人與海洋專家合作進行講授，內容涵蓋岩岸生態、物種識別、人工智慧程式、調查輔助方法和環境教育等主題。為了加強對海洋生物物種的印象，提供了先前在本區域調查的結果，包括 13 個分類門與 234 個海洋物種系統介紹（Table 4)，其中包括一種新的海洋扁蟲物種（Jie et al., 2016)，每種物種皆有圖像的記錄（Chen, 2011)。公民科學參與者受訓後須執行兩個任務：實地調查收集海洋生物資料及進行潮間帶環境教育解說。調查前，根據海洋保育署的穿越線調查方法，制定清晰的調查協議（survey protocol）路線。調查協議聚焦調查目標物種，並將參與者組織成指定小組來執行調查行動。在整個調查過程中，參與者沿著由穿越線所

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標記的預定路線進行，有系統拍攝所有目標物種，並將其數量記錄在調查表上。完成後，整理的數據和拍攝到的圖像整理，用於後續的人工智慧訓練。

3.2.2 訓練 AI 模型和效能評估

卷積神經網路(CNN)演算法是用於萃取影像特徵和識別的基礎（Fukushima, 1980）。R-CNN 和 YOLO 都建立在 CNN 框架之上，具有辨識出影像中的各種物件的能力（Redmon et al., 2016；Ren et al., 2016）。選擇 YOLOv5s 模型因其計算速度快，且能在自然環境中檢測海洋生物時精準度高。YOLOv5s 是種深度學習的機器視覺，需要有大量影像資料集進行訓練才能獲得辨識能力。從本研究的實地調查中所獲得的圖像，整理後每張圖像中經過標識標本的位置、大小和物種名稱。然後將這些標示的圖像整理成 YOLOv5s 的訓練資料集。所有資料集均隨機分割成 80%用於訓練，20%用於驗證。在配備 RTX3090-24G GPU 的 Linux 桌上型電腦上進行訓練與測試，使用的超參數（hypermeters）包括預訓練權重、訓練批次大小為 32、影像解析度為 800x800 以及學習回數設定為 200 回。

經過訓練的人工智慧模型需要執行 2 項任務。首先從影像中識別標本的實例（instance）的邊框（bounding box）位置，將其與其他物件區分開來，其次需能準確預測標本的類別名稱。人工智慧模型對任何目標標本的預測可分為以下 4 種結果：

1. 正確辨識目標物種－真陽性（TP）。
2. 準確地辨識目標以外的物種－真陰性（TN）。
3. 沒有正確辨識出目標物種－假陰性（FN）。
4. 錯誤地將不同物種辨識為目標物種－假陽性 (FP)。

欲區分 AI 模型對不同物種辨識是否造成混淆的情況，可用二維表來描述，通常稱之為混淆矩陣（Confusion Matrix）。在此矩陣中，實際物種在 x 軸上表示，而預測物種在 y 軸上表示（Fig. 9）。其餘另使用使用精確度、召回率與 mAP 公式評估整體模型的表現，詳細說明請參見 2.2.3 章節，此處不再重複敘述。

3.2.3 公民科學和 AI 的混合智慧協同性標準

國立臺灣大學

本研究採用 Dellermann 等人 (2019) 提出的混合智慧三個操作規範，以評估公民科學與人工智慧 AI 的混合智慧（Hybrid Intelligence, HI）協力程度：

1）集體性（Collectiveness）：當公民科學與人工智慧 AI 分別執行時的目標與協力系統的目標不同，兩者協作目的在共同解決問題，以實現設定的整合目標。

2）優越性（Solution superiority）：由公民科學和 AI 組成的「社群技術混合系統」（Socio-technical system）所達成的結果，應優於單獨（無論是公民科學還是人工智慧）所能達到的成果。

3）相互學習（Mutual learning）：隨時間展示出整體協力系統與公民科學和 AI 的進步，顯示雙方都持續在學習與發展中。

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3.3 結果

3.3.1 調查協議（Survey Protocol）內容與規範

為讓參與者達到科學調查的目的，設計調查協議（Survey Protocol）以確認所調查的品質能符合公民科學要求，在本研究中界定下列 3 項功能，以協助參與者完成所賦予的調查任務: 1. 導引調查海蝕平臺上生物多樣性時間與空間的變化; 2.導引蒐集海洋物種的影像以作為AI訓練使用 3.用作規劃環境教育的路線。根據文獻資料與自己的調查經驗，規劃建議調查協議（PSP），並對初次參與者舉辦調查與訓練 AI 的工作坊，賦予參與者調查與拍照紀錄出現海洋物種的能力與參與度。先訓練參與者學習辨識出海洋物種與如何拍照紀錄，然後根據 PSP 進行實地的調查與紀錄。在發現到目標物種，先前的習慣只是對於圖像的紀錄習慣是只拍幾張照片留下證據，而為了訓練 AI 需要大量的照片，根據第 2 章綠蠵龜的研究經驗，每一種海洋生物都需要蒐集至少 200 張以上的圖像，因此要求參與者拍攝盡量以不同角度與距離拍攝所遇到海洋生物的影像。除調查外，後續仍需用此 PSP 所規劃的路線與資料庫進行海洋環境教育。就在地環境教育的操作

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面來說，不可能一次就將所有發生的物種皆介紹完，而是希望找出常出現與特殊的海洋物種，而這都需要參與者共同進行，因而調查協議需設計成簡明、精準且容易操作。

根據海保署（2021）的岩礁生態調查方式，調整以穿越線（transect line）、紀錄調查的時間與空間分佈資料設計調查協議。時間資料主要以日期為主，分為春夏秋冬四個季節。由於調查侷限在低潮時刻，海蝕平台露出時 CSP 才能進行，空間資料主要以潮水高低程度（Tide level）來劃分高潮 (High Tide Level, HTL) 與低潮 (Low Tide Level, LTL) 的區分，當退潮時露出海蝕平台，生物出現在低窪仍舊積水處標記為 LTL，而出現在水面之上的標記為 HWL（Table 5）。

起初，調查協議改編自海保署（2021）的岩礁生態穿越調查方式。在確定的測量區內的海蝕平臺設置 10 條樣線。每個調查小組由兩名成員組成，沿著路線收集可用於 AI 訓練的影像，與記錄海洋生物出現的時間和空間生態資料。然而，在實際調查過程運作過程，起初的建議調查協議 (PSP)（Fig. 10a）發生一些問題，例如在夏季調查期間，海蝕平台在日曬與潮汐的關係下，常屬乾旱狀態，PSP

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路線無法發現藻類與海兔等物種，且又考慮到PSP的10條路線很難作為海洋環境教育路徑，需要修改，環形路線似乎比線性設計更合適，故產生了新的調適調查協議 (ASP) 的設計（Fig. 10b）。調適調查協議的修改主要在路線的改變，不再是直接從海岸穿越到大海，而順應沿著與海岸線平行的凹槽（GRV）行進（Fig. 10b）。這些凹槽可作為通往四個潮汐池（TP）和四個凹槽（GRV）的路徑。此修訂後的協議提供了小組規模的靈活性，調查者可按照路線非同步進行調查與環境活動。

3.3.2 建議調查協議（PSP）和AI模型訓練結果

從建議調查協議中的調查活動，收集整理9種不同物種計1,301張圖像與其空間和時間分佈資料，經過標識後生成2,643個實例（Fig. 11a）的訓練資料集，訓練成辨識效能精準度0.96175、召回率0.93533和$\text{mAP}_{0.5}$0.95485的PSP-YOLOv5s神經模型。其混淆矩陣的檢查，顯示大多數物種類別的真陽性 (TP) 值都很高。所有其他物種的 TP 值均超過 0.97，藤壺和牡蠣的TP值較低，分別為 0.83 和 0.87（Fig.11b）。

3.3.3 適調查協議（ASP）和 AI 模型訓練結果

將由 ASP 與 PSP 兩種調查協議下所獲得的影像整合，整理獲得 27 種海洋物種的類別、5,461 圖像、7,729 個實例的訓練集（Fig. 12b）。訓練出辨識效能精準度為 0.87412，召回率為 0.85843，平均精準度 mAP_0.5 0.8707 的 ASP-YOLOv5s 模型。在混淆矩陣分析中紅珊瑚藻（*Corallina* sp.）和海鞘（Tunicates）的真陽性（TP）值最低，只有 0.56 和 0.57。值得注意的是，PSP 中的大多數物種 TP 值保持不變。在 PSP-YOLOv5s 觀察到藤壺和牡蠣 TP 值略有改善，分別從 0.83 上升到 0.84 和 0.87 上升到 0.90（Fig. 12b）。

3.3.4 部署人工智慧提供辨識服務

將 AI 模型部署在伺服器待命，並用 Python-flask 程式語言開發應用程式介面 (API)，作為 AI 模型與使用者的通訊溝通（Fig. 13）。當使用者在自然棲息地遇到海洋生物時，使用者可以使用行動裝置拍攝照片並透過 API 上傳，讓 AI 模型

辨識，隨後將辨識結果傳回使用者（Fig. 14），此種簡化的流程提高科學調查和教育活動的效率和準確性。

3.4 討論

3.4.1 改善海洋生物多樣性調查方法

為執行海洋保育法中設立海洋保護區準備，海保署進行台灣與離島約 1,600 公里長的海岸線，岩礁潮間帶生態系統生物多樣性與保育調查計畫（海保署，2021）。在全台 67 個調查點中，進行評估了海岸環境和生物多樣性的評估調查。方法包括從高潮位到低潮位的 60m 拉穿越線。由 2 位調查人員在約 60 分鐘內，沿線記錄觀察，使用樣框攝影與採集海洋物種，記錄分析物種種類和其豐度。

然而，樣框內的攝影方法有其局限性，主要是會干擾到或是無法紀錄到游動性的物種（mobile），導致非固著生物（non-sessile species）的記錄不足。此方法也難以捕捉生物的季節性動態變化，如在三貂角 7 月初進行的調查記錄所示，由

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於夏季高溫條件，導致綠藻相的消退，導致攝食藻類動物不出現，結果可能顯著偏斜多樣性指數，遺漏關鍵動植物的依存性。

三貂角潮間帶區的地質複雜性，具有坑洞、溝槽、裂縫和岩石水池等不同棲息地，棲息地種類影響海洋生物多樣性。這些錯綜複雜的結構提供了眾多微棲息地，支持豐富的生物多樣性（Loke et al., 2016）。Davidson 等人（2004）發現，潮間帶固著生物表現出較大的數量豐度，但流動性生物類群的多樣性則是固著生物的兩倍。受到季風、潮汐、水溫和日照因素的影響，三貂角的生物多樣性可能出現出相當程度的空間和時間（Spatio-temporal）變化，絕非單一時間內、單一取樣穿越線調查所能反應出來。

本研究針對海洋生物空間和時間分佈的複雜性，透過公民科學參與者調查與回饋，調查協議從建議調查協議（PSP）修改為適應調查協議（ASP）（Fig. 10）。公民科學調查活動與調整路線，可解決海保署穿越線方法的時間、空間與調查人力資源的局限性。隨著修改隨機拉線調查路線，到沿著平台海溝裂縫與潮池單一路徑，更能符合實際微棲息地與生物多樣性的特性；並且，也允許參與者在其方

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便時間，進行不同時間的調查，靈活的方法擴展生物多樣性空間-時間動態數據的調查收集，亦考慮到減緩調查時因穿越槽溝對微棲息地踐踏損害，這對於監測生物多樣性變化與後續的環境教育產生更佳的解決方法。

3.4.2 公民科學與 AI 協力學習系統

在本研究中，逐步建立一個整合公民科學（CS）和人工智慧（AI）的協作學習系統。此系統促成了一種交互學習的關係，其中 AI 從人類調查到的影像訓練集獲益，而人類則通過 AI 的效能結果精煉公民科學所蒐集資料的品質，兩者形成一種持續的相互學習資訊流系統（Fig. 15）。公民科學參與者先在海洋生物辨識和 AI 訓練的工作坊，學習調查與環境教育的技能，隨後進行調查，共同收集了大量的調查圖像集，包括由 PSP 的 1,301 張圖像和來自 ASP 的 5,461 張圖像，用此數據來訓練出 PSP-YOLOv5s 和 ASP-YOLOv5s 兩個模型。訓練結果 PSP 的精準度為 0.96175，ASP 的精準度則為 0.87412，這反映在不同調查協議的參與者所集體收集數據的品質（Fig. 11 and 12）。

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從公民科學調查活動中收集到的海洋生物影像數據，訓練 AI 模型的海洋物種辨識能力，訓練後的 YOLOv5s 模型（Fig. 15c），訓練結果可反映訓練集資料的品質，積累公民科學經驗並提高後續資料的品質（Fig. 15d），這一反覆的過程更完善離線解決方案演算法（offline solution alagorithm）。公民科學參與者在調查或教育的過程中，除了在現場發現到的海洋生物，上傳影像即時利用部署在雲端的人工智慧模型（online solution algorithm）進行辨識（Fig. 15a, b），辨識圖像亦能用在提供下一步增強 AI 的辨識能力的訓練（Fig. 15e, f）。

維持公民科學計畫的重要關鍵，是如何維持蒐集數據的品質，此議題會因不同參與者的經驗水平差異而變得更為複雜 (Kosmala et al., 2016; Rosenthal et al., 2018; van der Velde et al., 2017)。本研究使用 AI 模型性能作為數據品質指標，能從個人智慧轉而對集體智慧的評估。參與 PSP 的參與者可能會質疑他們的 1,301 張圖像和 2,643 個實例資料集，是否有足夠的數據量訓練 PSP-YOLOv5s 模型？當得知具有 0.96175 精準度、0.93533 召回率以及平均精準度 $mAP_{0.5}$ 0.95485 的辨識性能，表示蒐集圖像數據的品質不錯。同樣地，當參與 ASP 整理出 5,461

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張圖像和 7,729 個實例，獲得 ASP 模型 0.87412 精準度、0.85843 召回率以及 0.8707 的 $mAP_{0.5}$，引發數據品質不佳的疑慮，是哪些因素造成的？

透過混淆矩陣可分析不同模型的數據品質，兩個模型的混淆矩陣的結果，詳列各類別的實例及其對應的真陽性（TP）數值（Table 5）。儘管紅珊瑚藻（*Corallina* sp.）和海鞘類（Tunicates）的訓練數據集中分別擁有 301 和 512 個實例，TP 值分別為 0.56 和 0.57。這與僅有 112 個實例的黑田海兔，在 ASP 數據集中獲得了 0.98 的 TP 值形成鮮明對比。這些差異顯示出 AI 模型在辨識某些海洋生物的不足，與數據品質有待改善，這凸顯公民科學參與者需學習改進某些數據的蒐集，提升調查與訓練資料的品質，才能獲得更佳的 AI 模型訓練成果。

3.4.3 發展混合智慧的過程

Dellermann 等人（2021）提出 3 個混合智慧系統的發展標準。第一個標準是在混合智慧（HI）的背景下的「集體性」（Collectiveness），指的是公民科學（CS）和人工智慧（AI）共同努力實現整合系統層面的目標。在本研究中，YOLO 物體

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檢測模型需要大量帶有標識的標本照片，以進行有效的模型訓練，此過程仰賴各個CS參與者在多次調查中逐步累積的數據收集。限於個人受限時間不足，加上海洋生物難以預測的出現時間而造成調查的不周全，AI模型成為一種聚合劑，能將不同時間蒐集到的生物多樣性資料整合，同時，將參與者的個人努力整合到共同目標上 — 全面記錄岩礁潮間帶生態系統的生物多樣性。

第二個混合智慧的標準，是達成比個別使用CS或AI更「優越成就」(Solution superiority)。對於個人而言，重複的調查和環境教育任務往往是繁重的，且無法明確指出調查數據的缺失，都可能造成挫折，減少參與者的熱情。然而，參與者持續的調查努力，有助於建構高品質的AI訓練集，再加上從利用AI的混淆矩陣可獲得的數據不足或品質不佳的回饋，可以針對缺點改進，維持參與者的調查動力並確保持續的參與，兩者結合將有助於整個計畫成功的運作。

最後第三個標準—建立「持續學習」（Mutual learning）成為混合智慧。AI的混淆矩陣結果可作為偵測特定物種數據品質的工具，間接鼓勵參與者補充不足之處與繼續努力蒐集數據。持續的蒐集過程不僅在正式調查期間進行，而且還能

通過在環境教育活動中，持續使用 AI 進行互動式海洋生物辨識與蒐集資料（Fig. 15）。可預期的是，隨著數據的積累，將逐漸完善訓練數據集，有益於提高 AI 對海洋生物的辨識能力。此外，AI 成為新手參與者的寶貴幫助，促進快速獲得物種識別技能，並持續促進公民科學社群的教育發展。

3.4.4 社會與科技的融合

本研究強調確保混合智慧的有效運行，需管理 AI 與 CS 之間的社會技術（socio-technology）整合。受到 McClure 等人（2020）的啟發，整理出 8 個關鍵屬性，以作為混合智慧為達海洋保護區任務的管理所需，以下敘述這些屬性及與 AI 和 CS 的相互關係，並在心智圖中顯出關係（Fig. 16）：

1. 主題魅力：

豐富的岩礁潮間帶生物多樣性與動態變化，為城市居民呈現出一幅生動且新奇的海洋圖景。這些海洋生物常具有色彩鮮明的外觀與活力，使該區域成為一個易於接近、神秘而迷人的接觸海洋新領域，吸引人們反覆造訪與探索。

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例如眼斑海兔（*Aplysia oculifera*）這種具有魅力的物種，其外觀與流行的卡通角色皮卡丘類似，對提高訪客與參與者和的來訪率發揮關鍵作用。這些吸引人的生物，加上結合 AI 工具的智慧型手機，一同用於搜尋與辨識，增強整體海洋生物多樣性探索的互動性和教育性，顯著提升海洋保護區設立的倡議和群眾的參與。

2. 主題識別：

對於一般海洋生物知識有限的遊客來說，欲辨識不同的海洋生物是個痛點。本研究根據先前調查，提出一個隨季節性變化可能出現的目標物種檢查表，聚焦在常見與特殊物種的辨識。讓遊客在造訪期間，能夠識別出所遇見的海洋生物，豐富他們與海洋生物多樣性的相遇，使辨識過程轉化成向海洋發問的學習體驗。

3. 民眾參與：

引入混合智慧驅動的線上 AI 辨識服務，遊客能夠通過與 AI 互動過程在潮間帶辨識海洋生物，不僅提供教育所需，也為了探索未知的海洋生物，以觀賞

取代捕撈海洋生物等危害行為，更可吸引更多民眾參與環境監護的行動，成為獲得民眾支持保育的關鍵。

4. 志願者參與：

志願者的奉獻參與是公民科學計劃成功與否的因素。儘管研究地點偏遠造成交通上的挑戰，但此處海洋生物多樣化出現的動態性質，常常激勵參與者的投入。將 AI 技術整合進調查中，當他們發現先前未記錄的物種時，亦能激發其參與熱情，也凸顯參與的價值和持續參與的重要性。

5. 參與者培訓：

為不同背景的參與者設計實用簡明的工作坊，俾使在無需專業知識下也能學習。運用以在地情況訂製的調查協議，和特別裁製的海洋生物物種檢查表，扼要說明複雜的海洋生物多樣性，且確保參與者都能持續使用 AI 輔助辨識的調查與環境教育。並定期安排實務討論聚會與社群媒體利用，可儘速回答與解決參與者所遇見的問題。

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6. 專業技術知識：

通過實地調查和與線上資源或海洋專家的互動，參與者專業知識的逐步提升，顯示混合智慧互動學習的過程。參與者也可透過訓練圖像的標識工作，學習如何訓練 AI，並能提供調查數據，增補後續 AI 訓練所需高品質的訓練集，以產出辨識能力更高的 AI 模型。

7. 數據敏感性：

對參與者上傳用於 AI 識別的圖像進行敏感處理。我們的調查協議確保使用者知道他們的調查後的圖像數據是保密的，僅用於增強 AI 模型。這種透明度對於維持信任和鼓勵負責任地分享數據。

8. 財務考慮：

財務議題主要考量是否要架設自用的 AI 電腦，或選擇購買雲端 AI 服務，兩者各有利弊，涉及的財務需求亦不同。本研究屬於建構自用的 AI 軟硬體電腦系統，以方便研究相關程式開發系統的靈活運用。然而，為實現達到持續

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調查與環境教育等保育目標，需要經費讓 HI 持續運作，運作 AI 電腦和公民科學計畫的財務需求，成為是否能達成保育目標的關鍵因素。

通過剖析和處理這些屬性，研究不僅提供了 AI-CS 整合的技術藍圖，還提供對支撐 HI 系統能否成功應用在環境保護的社會技術（Socio-technological）考慮。

3.4.5 混合智慧在設立海洋保護區中所扮演的角色

成立海洋保護區（MPA）不單是一項複雜的任務，後續根據其法規進行經營管理更是需要長時間與大量資源的工作。根據美國國家海洋保護區法的規定，成立 MPA 需考慮有效的管理措施，和承諾對該區域至少 10 年的全面監控調查（美國國家海洋與大氣管理局）。然而如何運用寶貴的人力資源，持續進行相對廣域的海洋生物多樣性調查是項縝密的工程。而根據海保署的報告討論中，也認定面臨人力持續調查的困境，諾能有志願者參與公民科學計畫，將可預期發揮出監測生物多樣性的關鍵作用（海保署，2021）。

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為整理調查數據以創建 AI 訓練集，公民科學參與者可以在指定區域內進行全年性一致性的調查。且透過此種公民科學綿密設計的調查方法，可提供海洋生態系統的時間和空間多樣性的詳細數據，為海岸生態的季節性模式，提供可靠的科學資料。

混合智慧（HI）為公民科學和人工智慧的協力作用，創建一個持續改善的架構，不僅可用於海洋生物多樣性教育，並激勵民眾參與定期的時空調查。在不同時間和位置收集數據的過程，可提供將來在設置 MPA 後，成為進行全面性民眾教育和持續收集生物多樣性數據的參考模式。

位處城市都會附近的海洋保護區，同時面臨期望大量訪客來訪與執法上的壓力，更衍生出廣泛的社會與生態經營管理挑戰。除了自然保育的考慮外，還需透過訪客量來協助當地漁業社區經濟活動的轉變，且郊區的生物多樣的保護區，其實也為城市居民提供了重新連接自然的機會，緩解緊張的城市生活條件帶來的壓力（Lefosse et al., 2023）。本研究提出這種社區和民眾的參與式混合智慧保育設

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計，亦可成為一種都會居民親生物（biophilic）工具，也回饋到城市的宜居性議題。

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第 4 章 結論與未來研究

人類世紀（Anthropocene Epoch）下的海岸自然資源管理挑戰，同時面對大量群眾造訪對環境衝擊與漁業經濟轉型的挑戰，人工智慧科技能夠提出一種新的符合永續發展的解決方法。近幾年，人工智慧科技雖發展神速，但應用在海洋或海岸資源的管理方興未艾，本論文提出嶄新的創見，探討如何運用人工智慧科技，構成群眾與人工智慧協同互學關係，以達到海洋自然資源的永續經營目標。

首先，本研究提出一套專為遊客量身設計，首次結合人工智慧物件偵測演算法的綠蠵龜保育方法。此研究方法包括從野外收集圖像、神經模型訓練、到 3 種 YOLO 神經模型（YOLOv3、YOLOv5s、YOLOv5l）辨識效益的評估，且實際部署最佳模型後評估其成效。研究發現，模型的訓練成效顯著受到訓練影像的數量與多樣化影響，當同一類別的訓練集超過 200 張多樣化影像，往往就能帶來模型正面的訓練成效，然而過大且重複性高的數據集，反而無法提升或甚至可能降低神經模型的訓練效能。值得注意的是，對於 YOLO 模型而言，在有限的訓練資料集下，僅考慮採用更新版本或增加神經層次的模型，並不能確保其辨識性

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能的提升。此發現對資源有限的管理機構提供重要的經驗，當要運用人工智慧影像辨識的功能時，將有限的時間與資金投資於蒐集多樣性，數量不用太多的影像，是種較為經濟且可行的策略。此外，此資料量與模型組合的效益研究，也對保育和研究那些難以接觸到的廣域性海洋生物具有重要價值，得以協助科學或管理機構開發出經濟又有效的人工智慧工具。

在促成公民科學和人工智慧的協作系統的研究，為三貂角的潮間帶生物多樣性保育提供永續解決方法。先由受過訓練的參與者進行野外調查，產生訓練人工智慧的影像資料集，而訓練成果除了能將海洋生物的影像數據轉化為指標數值，以便用以分析潮間帶生物多樣性，以及訓練資料的品質。當人工智慧模型訓練完畢後，在網絡上部署使用，除了作為探索調查海洋生物的工具，也支援公民科學參與者在環境教育中，對遊客提供海洋生物的解說，使用者與人工智慧持續互動促使混合智慧系統的演進，其中包括調整調查方法、特定物種的優先考慮及根據實地環境教育需求，修正更符合現況的人工智慧工具。策略性地管理此系統不僅促進了公民科學參與者的持續參與，也吸引更廣泛的民眾參與與支持，取得將該地區設立為海洋保護區的共識。

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無論小琉球遊客的海龜 AI 辨識與三貂角 AI 結合公民科學實驗性研究，都希望透過改變遊客的行為進行對海岸環境正面行為，符合聯合國永續生態指標（SDGs）第 12 項的「負責任消費與生產」（Responsible consumption and production）與第 14 項「保育及維護海洋資源」（Life below water），同時又兼顧當地漁村經濟從漁撈轉型到藍色遊憩經濟的第 8 項「良好工作及經濟成長」（Decent work and economic growth），希望這樣的研究模式能夠化解民眾對成立海洋保護區後可能造成經濟損失的疑慮。筆者先前在小琉球與三貂角馬崗社區，從事潮間帶解說員訓練多年，發現當環境解說帶來實質的經濟效益時，當地民眾會將保育的疑慮轉化成為對保育的熱情支持，因為深知設立保育管制遊客行為後，反而對在地的經濟會有更永續的幫助。

以目前 AI 辨識的科技來說，對於現場的解說運用還有許多不足與需要改善之處，展望未來運用 AI 科技的運用，須朝向更人性化、友善使用前進。近年來，以大型語言模型（LLM）演算法的生成式 AI（GAI）興起，得以處理自然語言，如聊天機器人的應用。作者已著手建構三貂角 LLM 的 AI 研究，過程還是需要

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公民科學參與者的協助，建構造訪時的問與答生態知識庫，用以微調（fine-tune）現有生成的 LLM，才能構成有用的混合智慧模式，希望不久的將來不僅有可辨識海洋生物多樣性的「眼」，更能有能聽懂與能回答海洋保育問題的混合智慧模式誕生。

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附表

Table 1. Number of instances of each class in the two training datasets after annotation (Chen et al., 2024a).

Dataset images	Class	Labeling names and instances numbers		
		GreenTurtle	redGT/young	marbleGT/elder
781image	1	685	NA	NA
	2	NA	481	212
	3	279	202	221
1462image	1	1287	NA	NA
	2	NA	678	609
	3	417	502	368

Here is 80% instances in training dataset

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Table 2. Performance of YOLOv3, YOLOv5s, and YOLOv5l as a function of dataset volume in terms of precision, recall, and F1-score (Chen et al., 2024a).

	YOLOv3			**YOLOv5s**			**YOLOv5l**		
	Precision	**Recall**	**F1-score**	**Precision**	**Recall**	**F1-score**	**Precision**	**Recall**	**F1-score**
781image	98.25%	97.68%	97.96%	98.72%	97.10%	97.90%	95.58%	95.37%	95.47%
1462image	96.90%	97.50%	97.19%	97.21%	97.82%	97.51%	95.71%	97.47%	96.58%

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Table 3. The instance $mAP_{0.5}$ scores and average class $mAP_{0.5}$ scores of various YOLO models as a function of class annotation settings. The plus and minus symbols indicate an increase or decrease in the $mAP_{0.5}$ scores when the number of instances was added (Chen et al., 2024a).

class number	**Single-class-setting**		**Two-class-setting**				**Three-class-setting**					
Neural model	**instances**	**GreenTurtle_1**	**instances**	**redGT/young_2**	**instances**	**marbleGT/elder_2**	**instances**	**redGT/young_3**	**instances**	**marbleGT/elder_3**	**instances**	**GreenTurtle_**
YOLOv3	685	98.3%	481	98.0%	212	95.6%	279	90.1%	202	91.5%	221	96.8%
	1287	98.7% +	678	94.5% −	609	97.1% +	417	89.4% −	502	88.4% −	368	97.5% +
YOLOv5s	685	99.0%	481	96.2%	212	93.1%	279	86.2%	202	91.3%	221	98.3%
	1287	99.1% +	678	93.3% −	609	94.3% +	417	89.9% −	502	83.3% −	368	98.2% −
YOLOv5l	685	98.2%	481	92.6%	212	87.9%	279	87.9%	202	82.6%	221	93.5%
	1287	98.6% +	678	93.1% +	609	95.6% +	417	89.2% +	502	79.9% +	368	98.6% +
average		98.6%		94.6%		93.9%		88.8%		86.2%		97.2%

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Table 4. The species list of marine species of Santiago bench complied from authors previous study (Chen, 2011).

Kingdom	Phylum	Common names	Species numbers
Animalia	Porifera	Sponges	8
	Bryozoa	Bryozoans, Moss Animals	4
	Mollusca	Cowries, Chitons, Sea Slugs, Octopuses, Oysters	72
	Arthropoda	Crabs, Shrimps, Barnacles	22
	Annelida	Segmented Worms	8
	Coelenterate	Corals, Sea Anemones, Jellyfishes	10
	Echinoderms	Sea Stars, Sea Urchins, Sea Cucumbers	27
	Nemertina	Ribbon Worms	2
	Platyhelminthes	Flatworms	8
	Chordata	Tunicates, Vertebrates, Fishes, Sea Snakes	39
Plantae	Chlorophyta	Green Algae	9
	Rhodophyta	Red Algae	19
	Chromophyta	Brown Algae	6

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Table 5. The instance amount and True Positive (TP) values of different species data collected by Proposal Survey Protocol (PSP) and Adaptive Survey Protocol (ASP) (Chen et al., 2024b).

common name	PSP		ASP	
	instance	species TP	instance	species TP
Eye Spot Sea Hare	499	0.97	489	0.97
Julian Sea Hare	210	0.98	210	0.98
Kurodai Sea Hare	112	1.00	112	0.98
Barnacle	812	0.83	804	0.84
Rock Oyster	205	0.87	205	0.90
Cowrie	276	1.00	276	0.96
Blotched Nerite	312	0.99	312	0.99
Blue-Ringed Octopus	145	1.00	145	0.94
Flat Rock Crab	72	1.00	72	1.00
Goby	NA		632	0.71
Chition	NA		195	0.93
Potamidids	NA		1266	0.87
Sargassum	NA		781	0.79
Sea Roach	NA		478	0.75
Crescent Grunter	NA		298	0.77
Sea Lettuce	NA		640	0.85
Swimming Crab	NA		275	0.96
Pebble Crab	NA		202	1.00
Xantho Crab	NA		192	0.98
Red Coral Algae (Corallina)	NA		301	0.56
Ballweed	NA		280	0.96
Sponge	NA		267	0.89
Tunicates	NA		512	0.57
Pyramid Periwinkle	NA		737	0.97
Brittle Star	NA		213	1.00
Damsel Fish	NA		221	0.78

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附圖

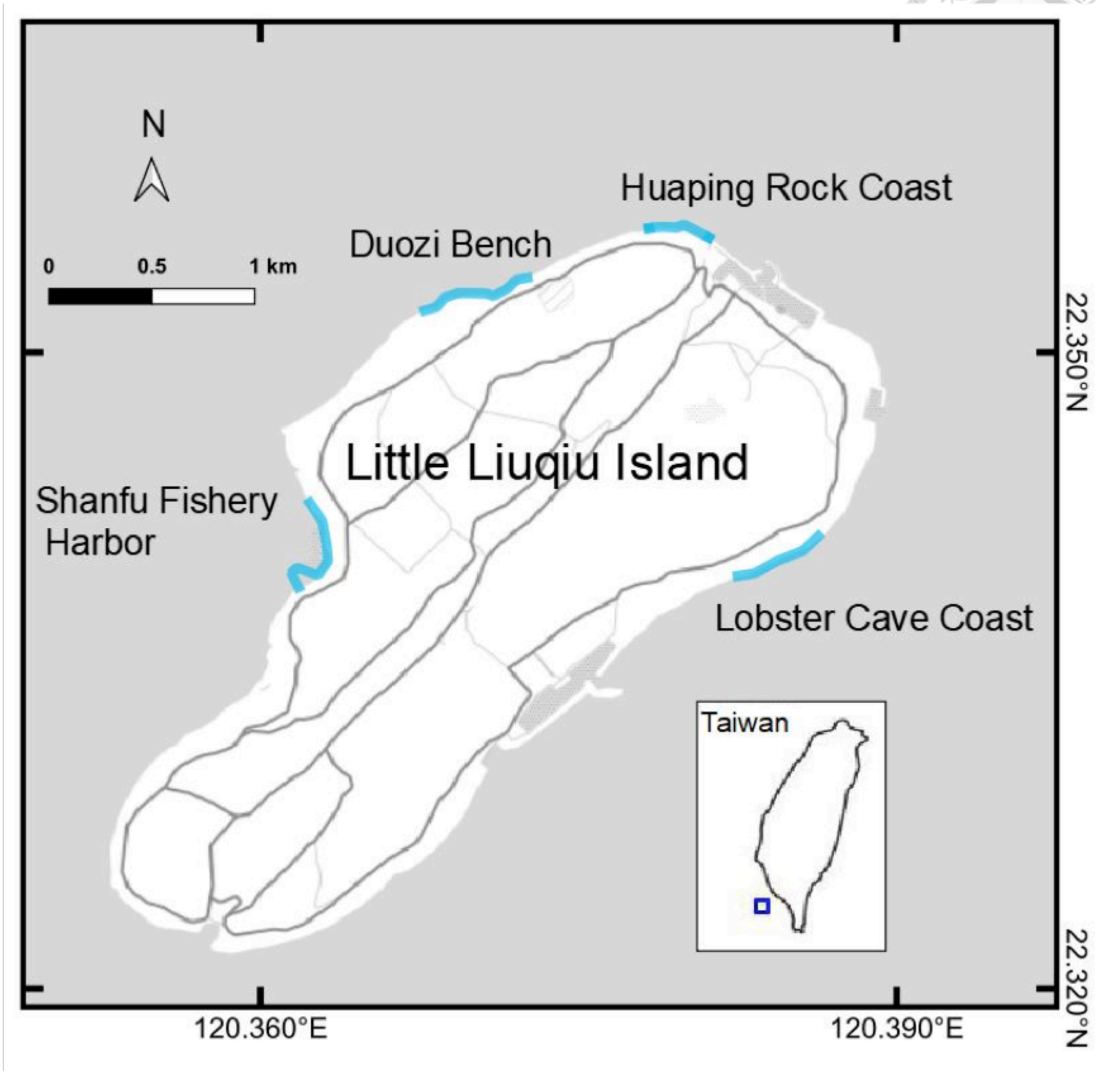


Fig. 1. Study sites around Little Liuqiu Island and the location of the island adjacent to Taiwan (inset) (Chen et al., 2024a).

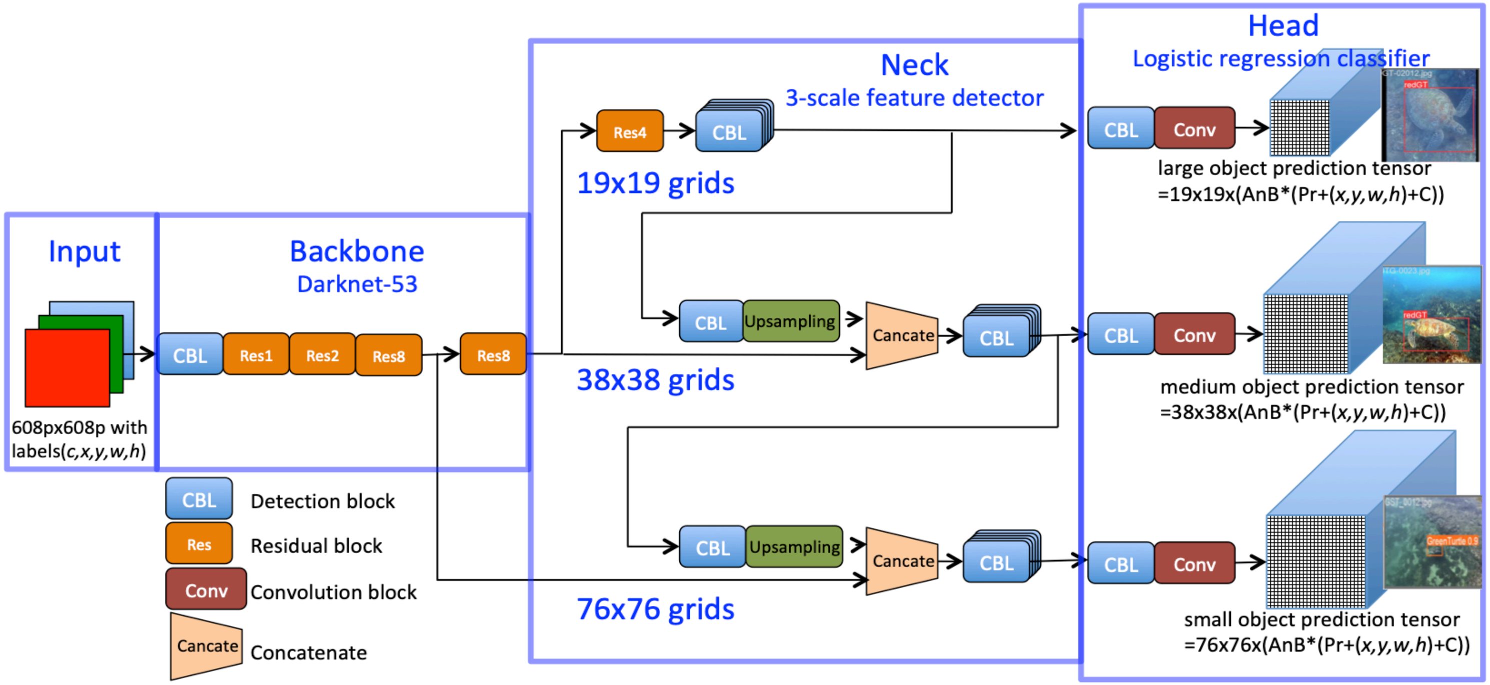
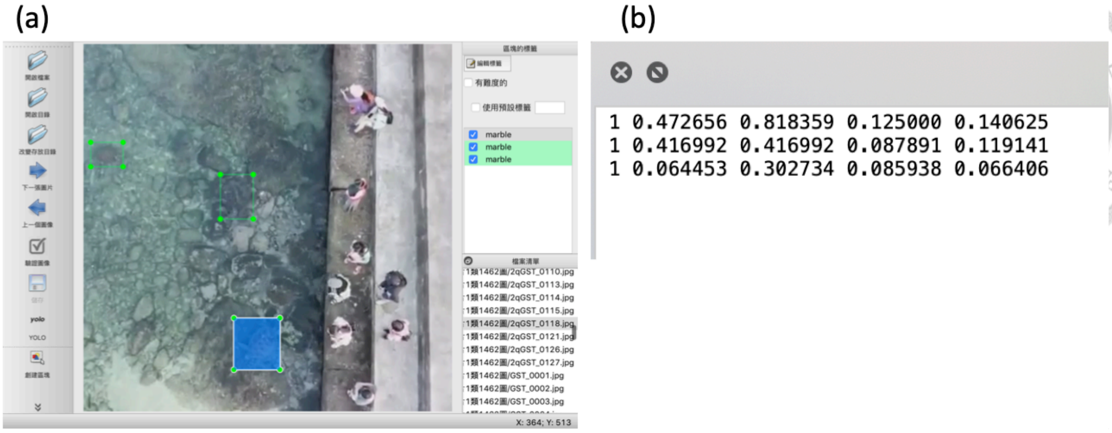


Fig. 2. Architecture and data pipeline stage of YOLOv3. The architecture consists of four main components: "Input," "Backbone," "Neck," and "Head." The "Backbone" component is responsible for performing feature extraction on the input image. The "Neck" component carries out multi-scale feature detection across three scales: 19x19 grids, 38x38 grids, and 76x76 grids. Finally, the "Head" component functions as a logistic regression classifier to predict object labels, positions, bounding sizes, and class probabilities for objects present in the input image (Chen et al., 2024a).



```
1 0.472656 0.818359 0.125000 0.140625
1 0.416992 0.416992 0.087891 0.119141
1 0.064453 0.302734 0.085938 0.066406
```

Fig. 3. Three instance examples of one object class after labeling via (a) bounding boxes as ground-truth objects; (b) Corresponding coding data, codes created in the form of (*c, x, y, w, h*) after annotation (Chen et al., 2024a).

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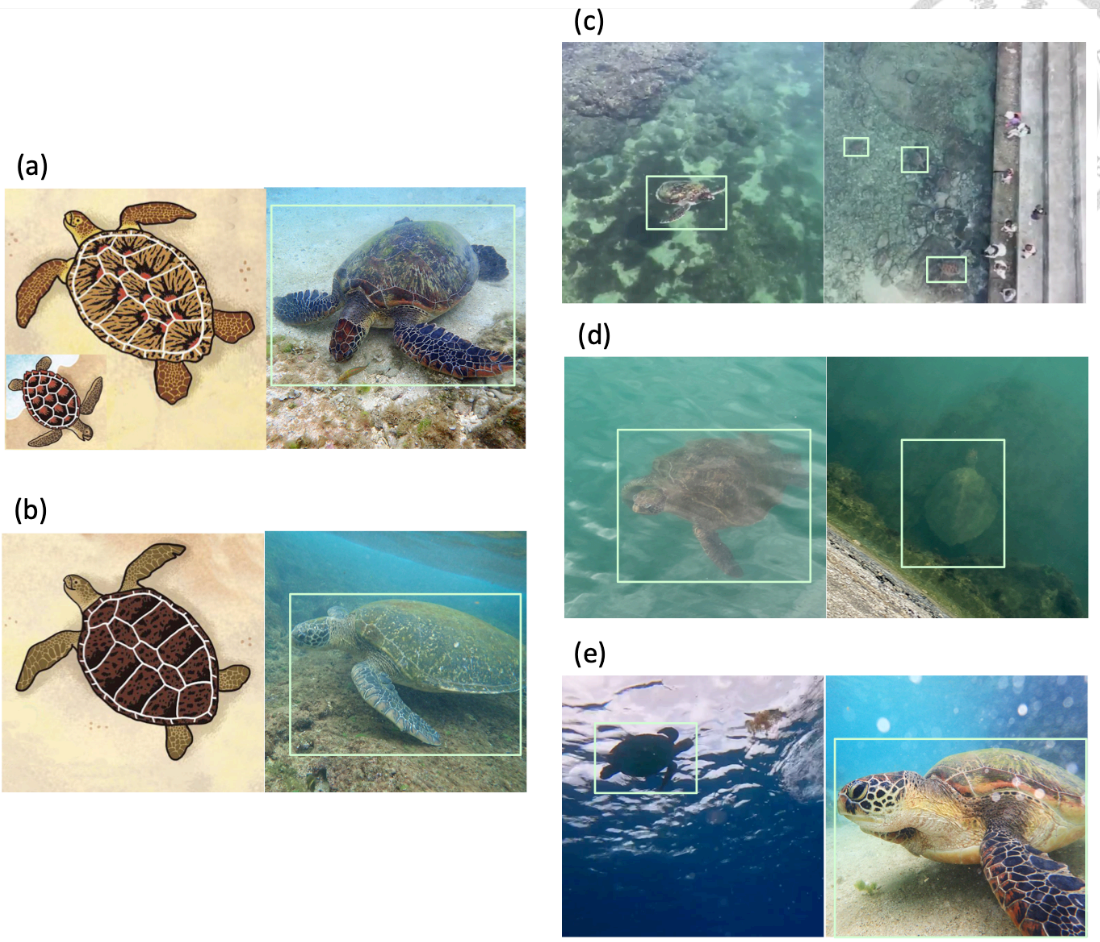

Fig. 4. Feature patterns used for annotating label classes: (a) redGT/young patterns indicative of juvenile or subadult; (b) marbleGT/older pattern indicative of adult (> 30 years); (c) Images from UAV drone; (d) Turtles obscured by murky water and surface reflections hindering identification; (e) Backlight and turtle's body part (Chen et al., 2024a).

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(a)

	average instances/class	F1-score YOLOv3	F1-score YOLOv5s	F1-score YOLOv5l	mAP0.5 YOLOv3	mAP0.5 YOLOv5s	mAP0.5 YOLOv5l	mAP0.5:0.05:0.95 YOLOv3	mAP0.5:0.05:0.95 YOLOv5s	mAP0.5:0.05:0.95 YOLOv5l
1462image 1 class	1287	97.2%	97.5%	96.6%	98.6%	99.1%	98.6%	72.9%	72.3%	66.0%
781image 1 class	685	98.0%	97.9%	95.5%	98.3%	99.0%	98.2%	67.7%	65.7%	59.4%
1462image 2 class	644	90.3%	91.4%	89.6%	90.8%	93.8%	94.3%	64.9%	66.8%	61.3%
1462image 3 class	429	86.1%	87.2%	85.7%	87.2%	90.5%	89.2%	63.4%	63.4%	54.2%
781image 2 class	347	88.8%	90.7%	87.4%	90.2%	94.6%	90.2%	57.2%	59.2%	53.6%
781image 3 class	234	89.7%	88.9%	85.2%	91.8%	91.9%	88.0%	57.8%	58.8%	51.6%

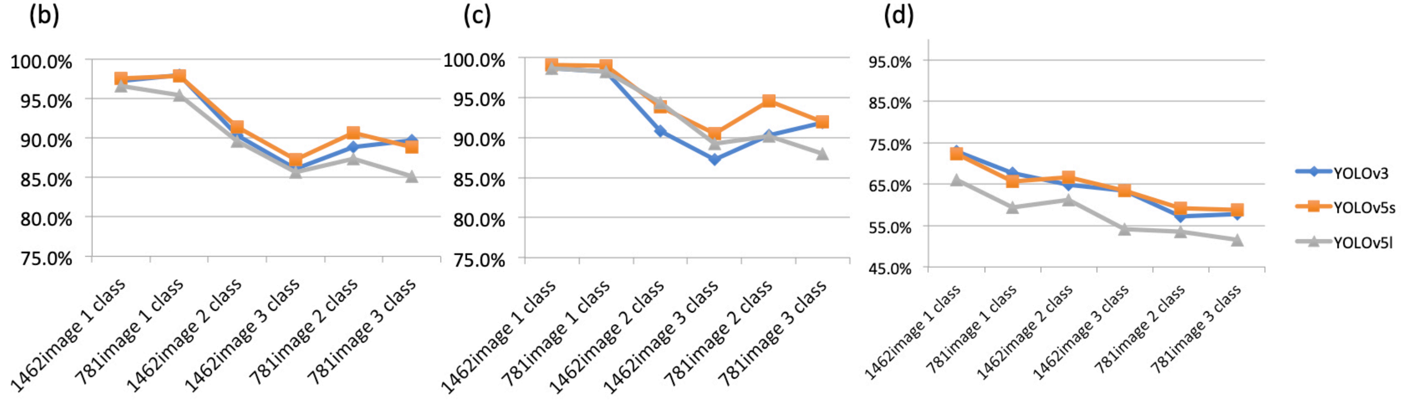


Fig. 5. Performance indicators for all experiment scenarios in this study: (a) Performance comparison of YOLOv3, YOLOv5s, and YOLOv5l; (b) F1-score, (c) mAP$_{0.5}$, and (d) mAP$_{0.5:0.05:0.95}$ (Chen et al., 2024a).

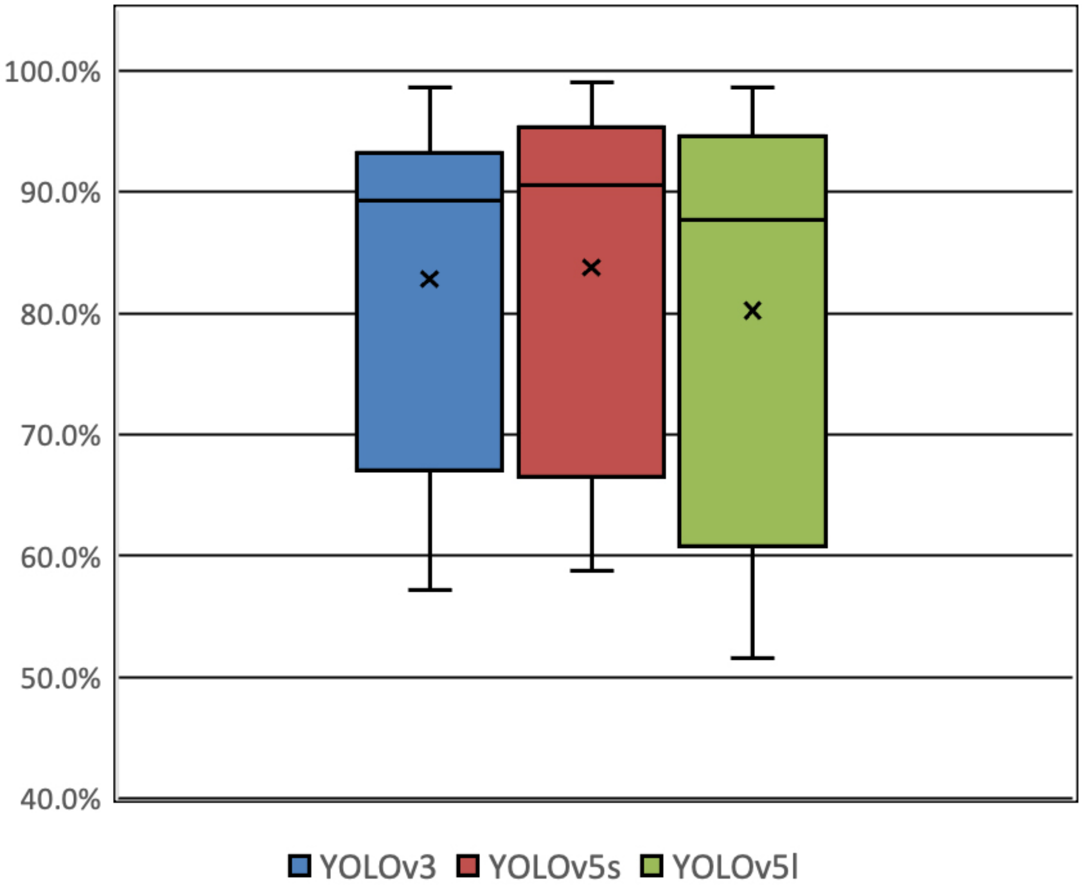
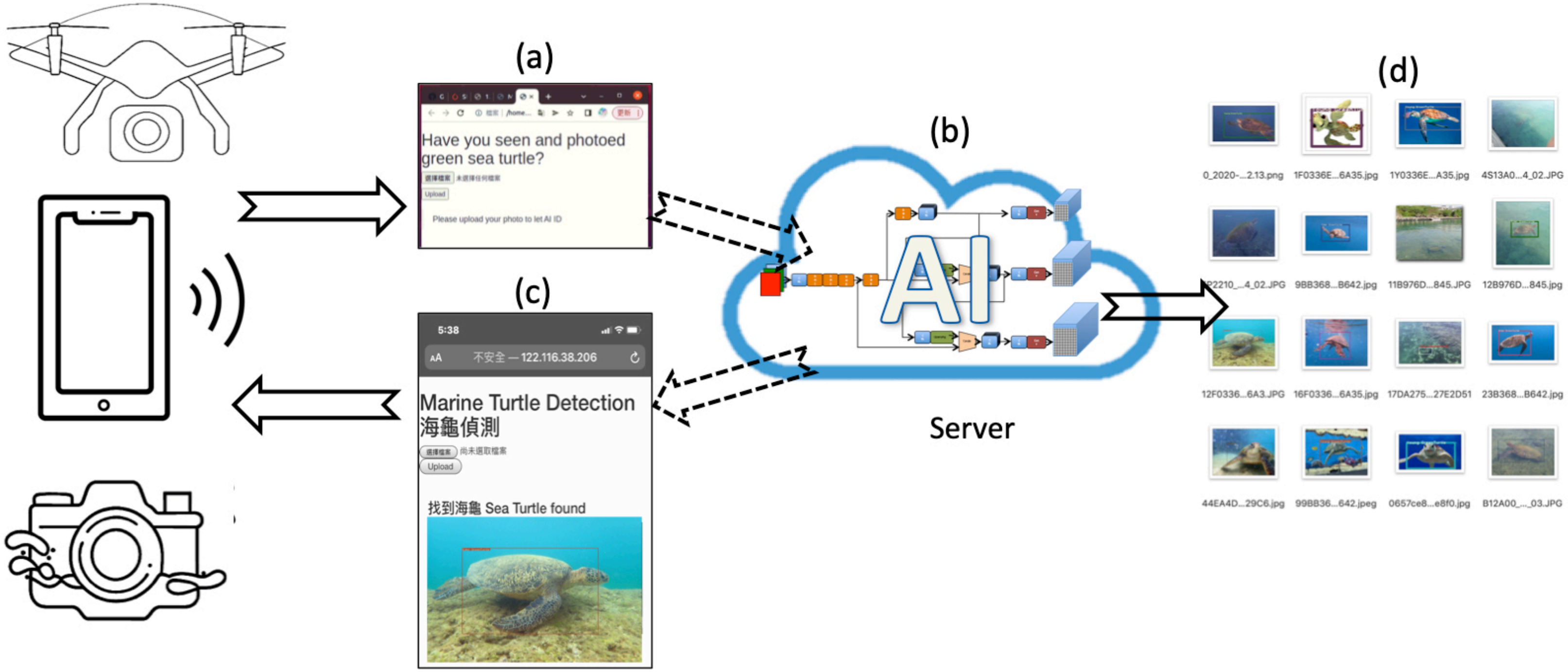


Fig. 6. Boxplot of F1-score, $mAP_{0.5}$, and $mAP_{0.5:0.05:0.95}$ based on all experiment results using YOLOv3, YOLOv5s, and YOLOv5l (Chen et al., 2024a).



Have you seen and photoed green sea turtle?

Upload

Please upload your photo to let AI ID

5:38

不安全 — 122.116.38.206

Marine Turtle Detection 海龜偵測

Upload

找到海龜 Sea Turtle found

Fig. 7. The architecture and information flow of AI detection service for green sea turtles detection. (a) Images are sent as queries via user interface API, (b) then upload to AI neural model for green sea turtle detection. (c) Identification results are sent back to users through user interface API, and all queries and results are stored on servers, (d) examples of detected images uploaded by various users (Chen et al., 2024a).

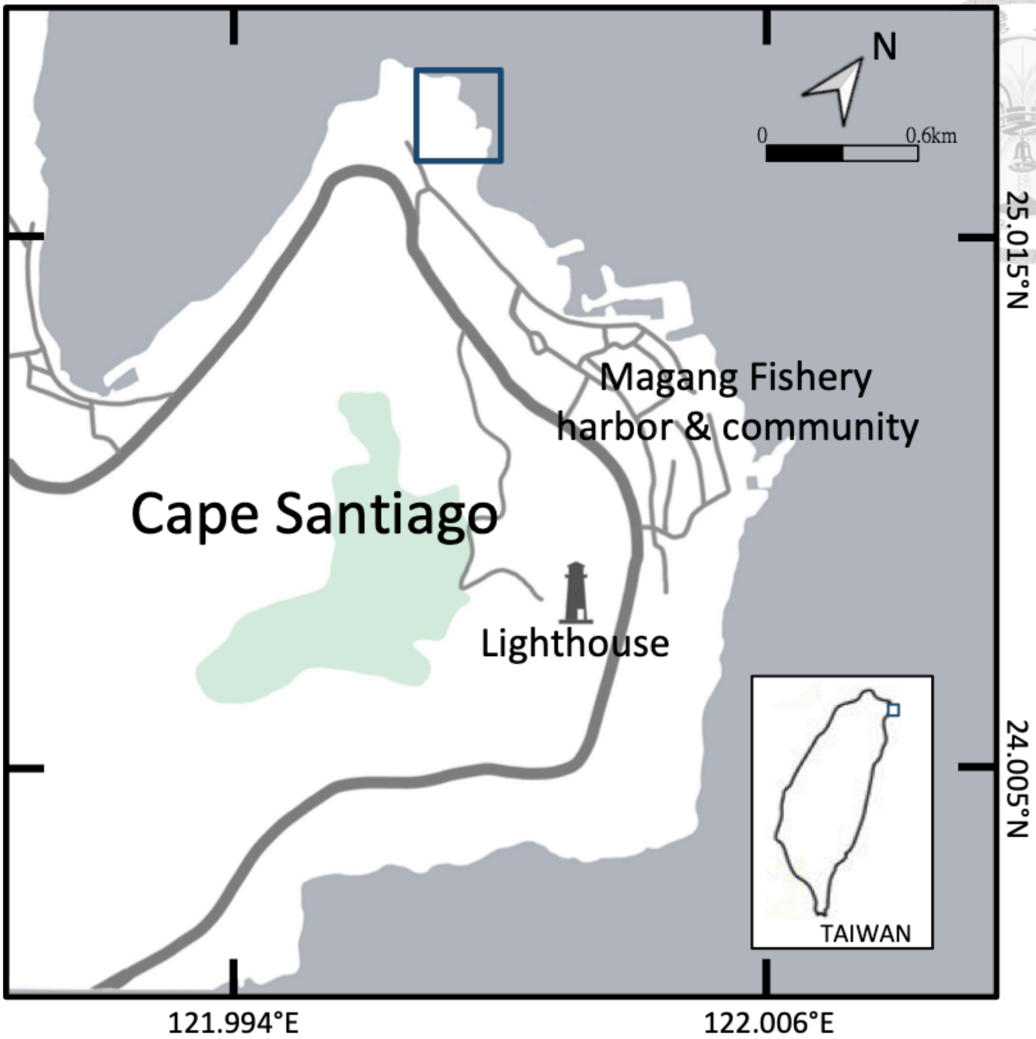


Fig. 8. Location of the study site at Cape Santiago with its position within Taiwan highlighted (inset) (Chen et al., 2024b).

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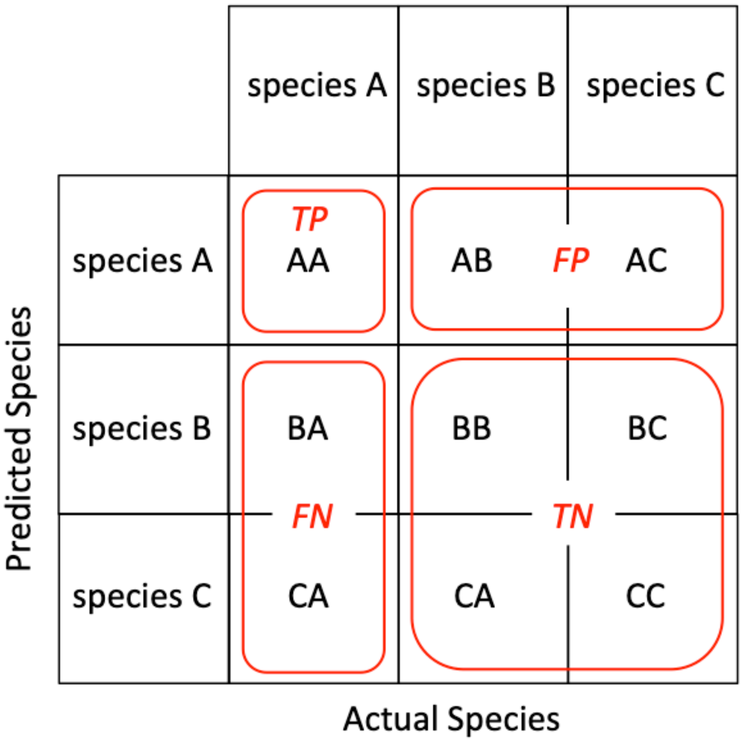

Fig. 9. An example of 3x3 Multi-Class confusion matrix with actual species as X-axis/row-grids and predicted species as Y-axis/column-grids. While focus on class A, the AA grid is True Positive, TP, the rest row grids are False Positive, FP, the rest column grids are False Negative, FN, and the rest grids, except all above grids, are all True Negative, TN (Chen et al., 2024b).

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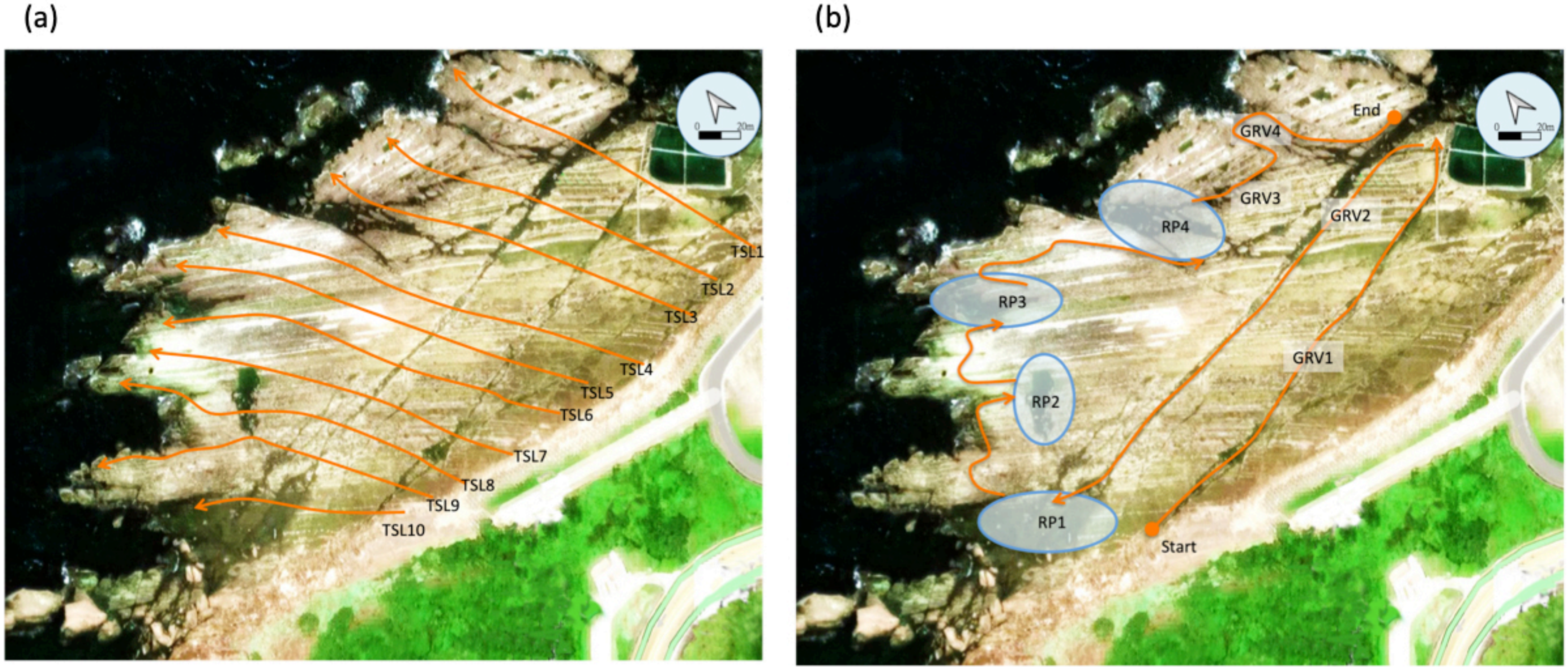

Fig. 10. The survey transect routes of different survey protocols. (a) The routes of ten transect lines (TSL) of proposed survey protocol (PSP), and (b) a loop comprised of 4 grooves (GRV) and 4 rock pools (RP) of adaptive survey protocol (ASP) (Chen et al., 2024b).

(a)

Phylum	Common names	Scientific names	Spatial	Temporal	Instances
Mollusca	Eye Spot Sea Hare	*Aplysia oculifera*	HWL	W, SP, F	499
	Julian Sea Hare	*Aplysia juliana*	HWL	W, SP, F	210
	Kurodai Sea Hare	*Aplysia kurodai*	LWL	W, SP, F	112
	Rock Oyster	*Saccostrea mordax*	HWL	W, SP, SU, F	205
	Cowrie	*Cypraea annulus*	LWL	W, SP, SU, F	276
	Blotched Nerite	*Nerita albicilla*	HWL	W, SP, SU, F	312
	Blue-Ringed Octopus	*Hapalochlaena cf. fasciata*	LWL	SU, F	145
Arthropoda	Flat Rock Crab	*Percnon planissimum*	HWL	SU, F	72
	Barnacle	*Tetraclita kuroshioensis*	HWL	W, SP, SU, F	812

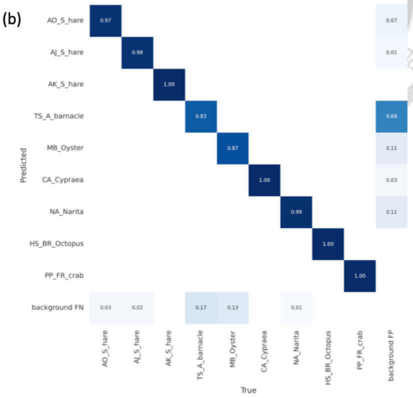

Fig. 11. (a) The species name, scientific name, spatial-temporal and instance number of 9 species for training YOLOv3 after proposal protocol surveys by CS participants. (b) Confusion matrix results for different species class classification (Chen et al., 2024b).

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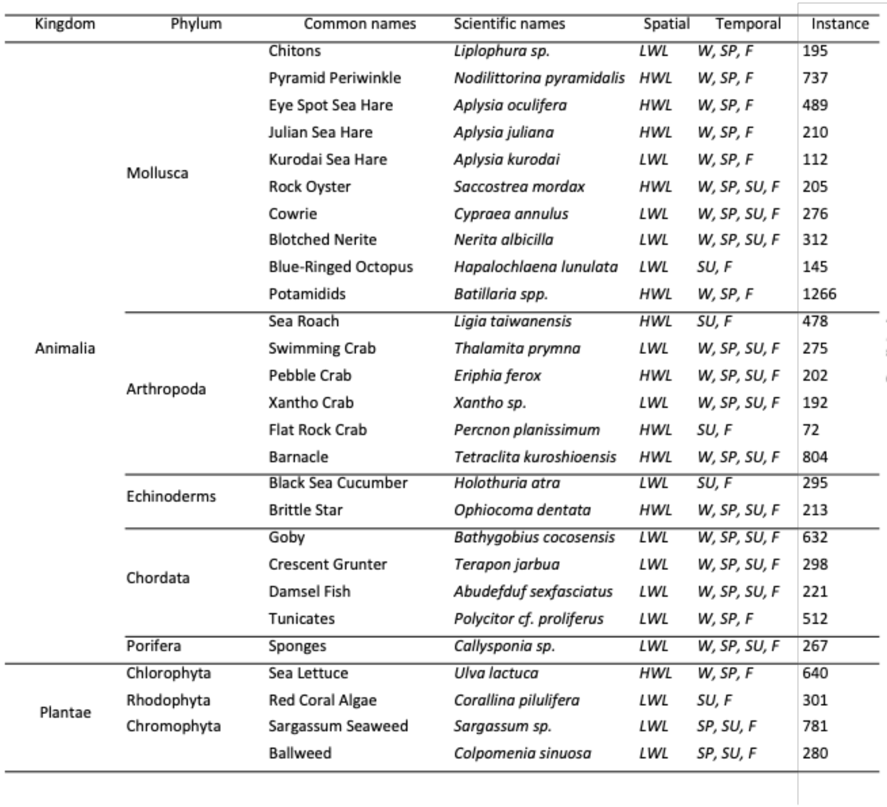
(a)



Kingdom	Phylum	Common names	Scientific names	Spatial	Temporal	Instance
Animalia	Mollusca	Chitons	*Liplophura sp.*	*LWL*	*W, SP, F*	195
		Pyramid Periwinkle	*Nodilittorina pyramidalis*	*HWL*	*W, SP, F*	737
		Eye Spot Sea Hare	*Aplysia oculifera*	*HWL*	*W, SP, F*	489
		Julian Sea Hare	*Aplysia juliana*	*HWL*	*W, SP, F*	210
		Kurodai Sea Hare	*Aplysia kurodai*	*LWL*	*W, SP, F*	112
		Rock Oyster	*Saccostrea mordax*	*HWL*	*W, SP, SU, F*	205
		Cowrie	*Cypraea annulus*	*LWL*	*W, SP, SU, F*	276
		Blotched Nerite	*Nerita albicilla*	*LWL*	*W, SP, SU, F*	312
		Blue-Ringed Octopus	*Hapalochlaena lunulata*	*LWL*	*SU, F*	145
		Potamidids	*Batillaria spp.*	*HWL*	*W, SP, F*	1266
	Arthropoda	Sea Roach	*Ligia taiwanensis*	*HWL*	*SU, F*	478
		Swimming Crab	*Thalamita prymna*	*LWL*	*W, SP, SU, F*	275
		Pebble Crab	*Eriphia ferox*	*HWL*	*W, SP, SU, F*	202
		Xantho Crab	*Xantho sp.*	*LWL*	*W, SP, SU, F*	192
		Flat Rock Crab	*Percnon planissimum*	*HWL*	*SU, F*	72
		Barnacle	*Tetraclita kuroshioensis*	*HWL*	*W, SP, SU, F*	804
	Echinoderms	Black Sea Cucumber	*Holothuria atra*	*LWL*	*SU, F*	295
		Brittle Star	*Ophiocoma dentata*	*HWL*	*W, SP, SU, F*	213
	Chordata	Goby	*Bathygobius cocosensis*	*LWL*	*W, SP, SU, F*	632
		Crescent Grunter	*Terapon jarbua*	*LWL*	*W, SP, SU, F*	298
		Damsel Fish	*Abudefduf sexfasciatus*	*LWL*	*W, SP, SU, F*	221
		Tunicates	*Polycitor cf. proliferus*	*LWL*	*W, SP, F*	512
	Porifera	Sponges	*Callysponia sp.*	*LWL*	*W, SP, SU, F*	267
Plantae	Chlorophyta	Sea Lettuce	*Ulva lactuca*	*HWL*	*W, SP, F*	640
	Rhodophyta	Red Coral Algae	*Corallina pilulifera*	*LWL*	*SU, F*	301
	Chromophyta	Sargassum Seaweed	*Sargassum sp.*	*LWL*	*SP, SU, F*	781
		Ballweed	*Colpomenia sinuosa*	*LWL*	*SP, SU, F*	280

(b)

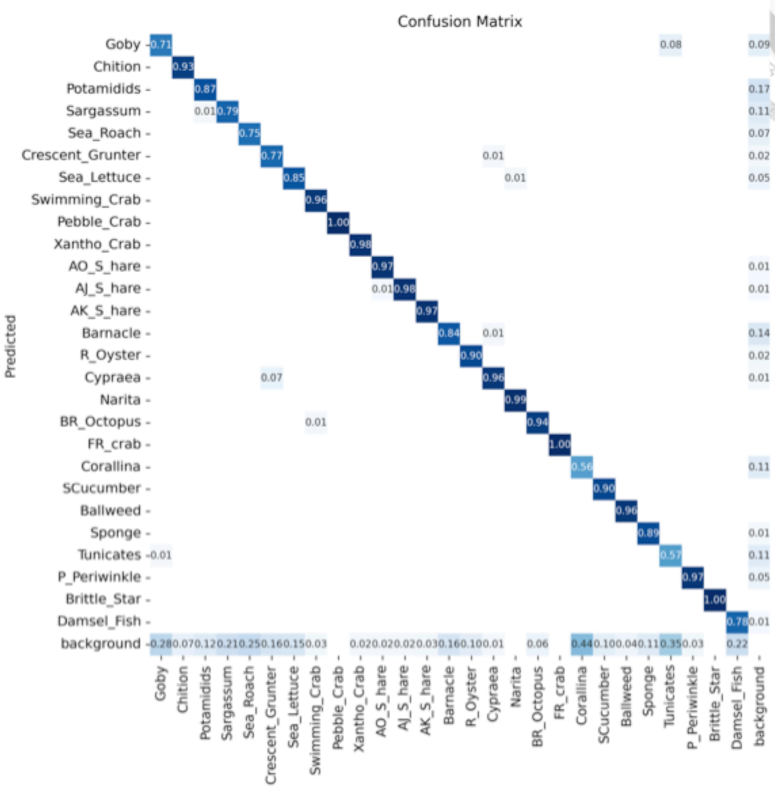


Fig. 12. (a) The species name, scientific name, spatial-temporal and instance number of 27 species for training YOLOv3 after adaptive protocol surveys by CS participants. (b) Confusion matrix results for different species class classification (Chen et al., 2024b).

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Fig. 13. The program interface API incorporates an AI recognition service. Users can utilize the provided species recognition capabilities to search for species in the field. When they encounter a suspected species, they can capture a photo and upload it from their mobile phones to the server to request AI identification (Chen et al., 2024b).

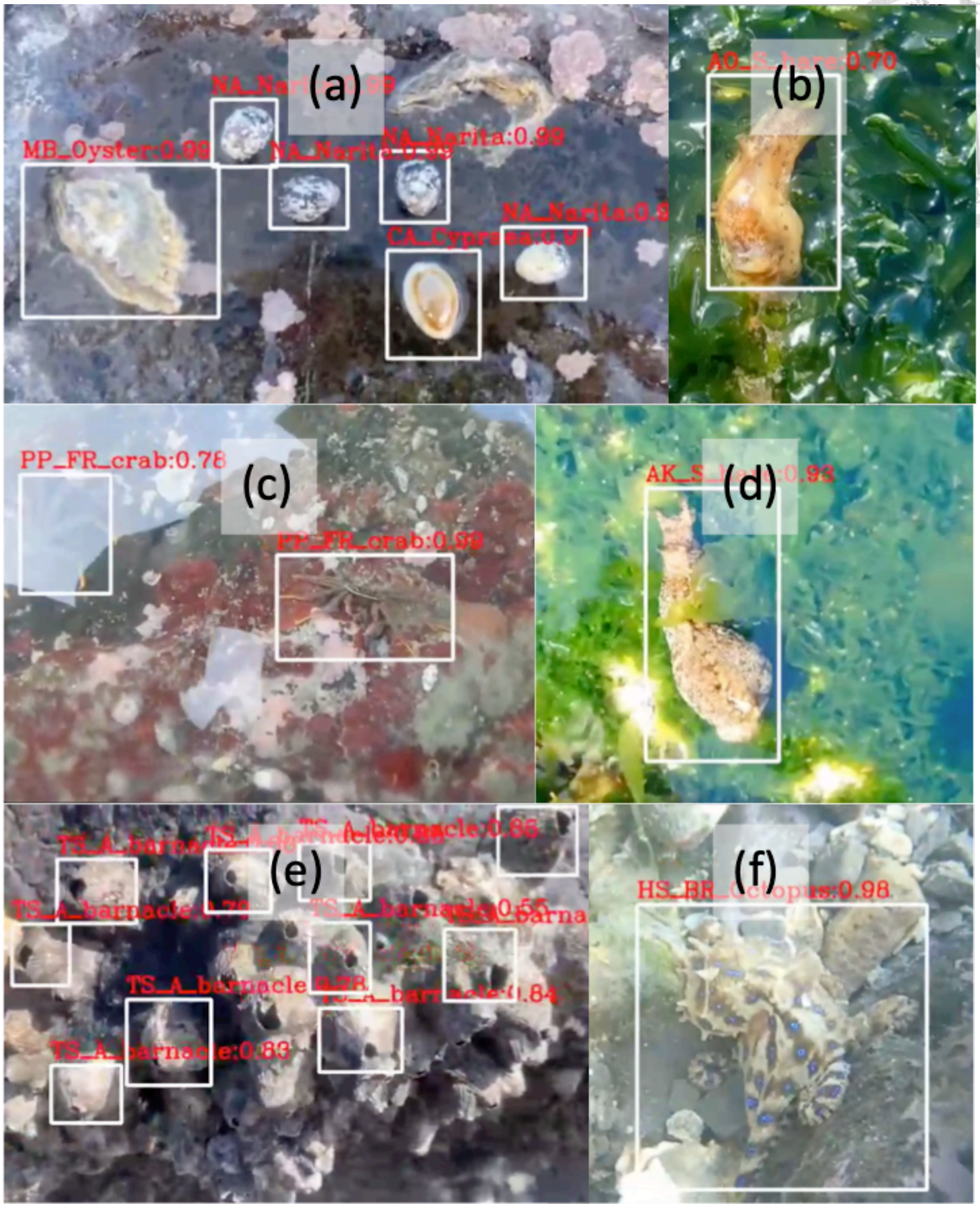

Fig. 14. Examples of identified species instances (a) 4 blotched-nrites, 1 cowrie and 1 rocky oyster, (b) 1 eye spot sea hare, (c) 2 flat rock crabs, (d) 1 kurodai sea hare, (e) 10 barnacles, (f) blue-ringed octopus (Chen et al., 2024b).

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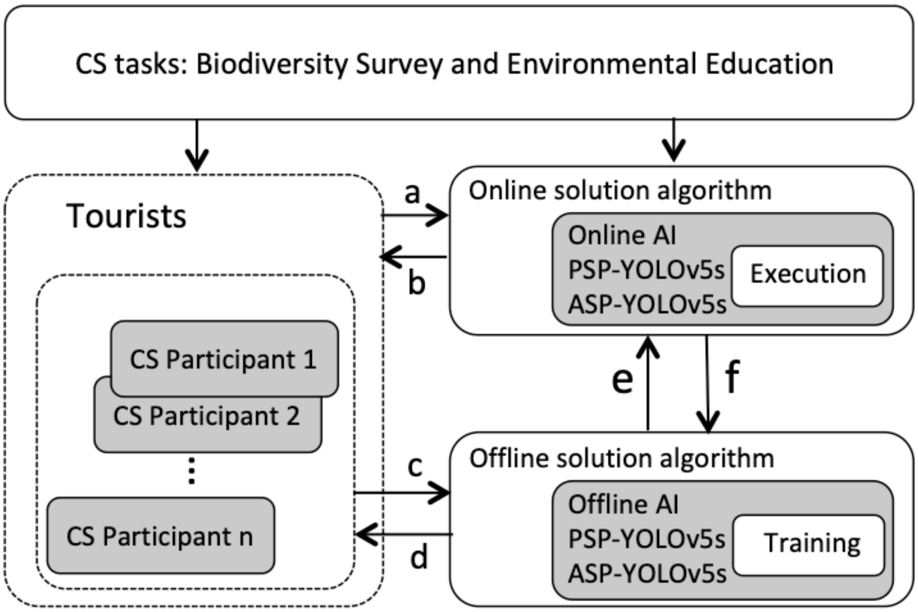

Fig. 15. The Information Flow Diagram (IFD) illustrating "Tier 3: Hybrid Intelligence (HI) at the collective level" adapted from Rafner et al., 2021. Please refer to the accompanying text for details (Chen et al., 2024b).

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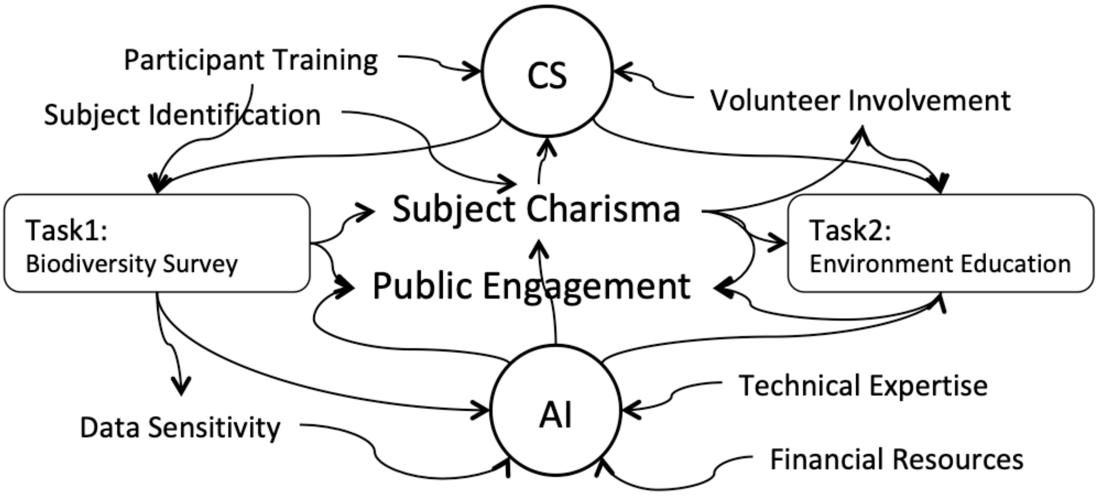

Fig. 16. Illustration depicts the integrative mind map of the Hybrid Intelligence system, encompassing components of CS and AI, along with two distinct tasks. The map is further characterized by eight attributes crucial for effective system management. The directional arrows within the diagram indicate the influences between components and attributes. Detailed explanations can be found in the accompanying text (Chen et al., 2024b).

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附錄：本論文已發表之學術文章

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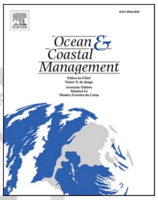

Enhancing green sea turtle (*Chelonia mydas*) conservation for tourists at Little Liuqiu island, Taiwan: Application of deep learning algorithms

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ABSTRACT

Observing marine life has emerged as a pivotal catalyst for the growth of the Blue Economy. Yet, overzealous and recurrent observations may exert undue stress on marine creatures, thereby complicating the sustainable management of marine assets. After the easing of Covid-19 pandemic restrictions, a notable influx of tourists to Little Liuqiu Island, Taiwan puts considerable stress on its green sea turtle population. This surge intensified incidents of illegal harassment, triggering concerns from both the local community and administrative bodies. The prevailing challenge is to ensure tourists observe these turtles with respect, refraining from behaviors such as touching or pursuing them. Addressing this, our study harnesses deep learning algorithms to equip ecotourism operators and tourists with tools to detect green sea turtles across diverse coastal terrains, reinforcing conservation efforts. Our analysis scrutinized object detection AI models, namely YOLOv3, YOLOv5s, and YOLOv5l. Fieldwork was undertaken on the island to gather ample training images, capturing elusive green sea turtles in various settings, from coastline strolls to drone imagery. Supplemental images sourced from local social media platforms were later added. Contrary to expectations, we found that merely expanding the training dataset did not guarantee improved outcomes. Instead, the variance in image content, considering distances, angles, and turtle appearances, played a pivotal role in enhancing model precision. Through our experimentation, the streamlined YOLOv5s model consistently eclipsed its more complex counterparts in performance. An AI service, underpinned by the YOLOv5s model, has been launched to distinguish between green sea turtle types for tourist-focused conservation initiatives. Future iterations will incorporate user feedback to refine accuracy. Our research breaks new ground, spotlighting the intricacies of gathering natural environment data, pinpointing optimal AI models, and evaluating their practical implications for green sea turtle conservation.

1. Introduction

Ocean or coastal tourism is considered a part of the Blue Economy (World Bank, 2017) and aligns with sustainable ocean management policies that promote the development of island nations (Bhattacharya and Dash, 2021). Marine creature sightings have become a global phenomenon and have made substantial contributions to local economies (Scuderi et al., 2022). For example, whale-watching activities generated an annual revenue of $3 million in northern Peru (Guidino et al., 2020), and nature-based marine tourism in the Gulf of California attracted an estimated 896,000 visitors per year, resulting in $518 million in revenue and directly supporting 3575 jobs (Cisneros-Montemayor et al., 2020). For marine researchers and managers, monitoring the temporal and spatial patterns of marine life populations is a formidable task. However, this monitoring information is crucial for effective marine or coastal resource management. Paradoxically, the elusiveness and unpredictability of marine life can be a draw for ecotourism, motivating citizens to invest their time, resources, and efforts in seeking out cryptic, rare, or endangered species. Once discovered, these species are often photographed and shared on social media using smartphones. The content of these posts, including images, videos, timestamps, and geographic data, can serve as valuable references for ecological monitoring and conservation management (Toivonen et al., 2019; Elqadi et al., 2017; Cranswick et al., 2022).

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The decline in sea turtle populations has historically been linked to the harvesting of their meat, eggs, and shells (Chaloupka et al., 2008). Recent studies, however, reveal a more complex scenario. Factors such as climate change, which impacts turtle sex determination (Heppell et al., 2022), habitat pollution (Sposato et al., 2021), and various other anthropogenic pressures have also contributed significantly to their dwindling numbers. In response, Marine Protected Areas (MPAs) and Marine National Parks have emerged as crucial sanctuaries. These areas offer green sea turtles safe zones for feeding, breeding, and nesting with minimal human interference, enabling focused and effective conservation efforts for the endangered species.

The regulation of international trade in green sea turtle products is governed by the Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES), highlighting the global commitment to their conservation. Specific zoning within MPAs, such as the 'B' Zone in Marine National Parks, enforces a 'look but don't take' policy, prohibiting extraction (Day, 2002). The Tortuguero National Park in Costa Rica exemplifies this approach as a key breeding ground for green sea turtles in the Western Hemisphere, with strict controls on human activity and lighting during nesting seasons, and a total ban on the extraction or harassment of sea turtles (Gutiérrez-Lince et al., 2021). Similarly, in Taiwan, the Wildlife Conservation Act stringently prohibits trading, capturing, harvesting, or harassing marine turtles in any coastal or marine area (Wildlife Conservation Act, Taiwan).

Ecotourism is one approach to compensating for the economic constraints imposed by wildlife conservation. According to Weaver and Lawton (2007), ecotourism is a nature-based tourism that benefits conservation efforts and the welfare of local residents. Pegas et al. (2013) reviewed operating ecotourism cases of sea turtles and concluded the importance of incentives of local communities cooperation and involvement, which will initiate the change of utilization way and lead to reduced consumption of natural resources and/or increased conservation support. The success of sea turtle ecotourism often depends on visitors' on-site experience, which involves environmental education and the sighting of sea turtles (Tisdell and Wilson, 2005). Lamb (2019) reported that visitors' embodied encounters with sea turtles experience sharing through online remediation on social media, like Instagram and Facebook, had effectively promoting sea turtle tourism at Laniākea Beach, Hawaii. Therefore, accurate estimates and on-site of sea turtle encounters will be very helpful for promoting sustainable ecotourism operations.

Deep learning is an AI algorithm that utilizes multi-layered neural networks to analyze and process data intricacies, enabling image pattern recognition and decision-making. The training process is pivotal, as the model's efficacy largely hinges on the quality and depth of its training (Own-Bar and Trivedi, 2017; Wei et al., 2018). While pre-trained neural models can assist in the transfer and learning processes, there remains a need for a specific dataset tailored to new learning scenarios (Ozbulak et al., 2016; Windrim et al., 2016). To detect green sea turtles in their natural habitat, it is crucial for the model to encompass various animal features, including camouflage against the background, rapid changes in environmental conditions (such as waves and lighting), and the different idiosyncrasies present in the images (such as noise, brightness, and chroma). Therefore, collecting a suitable animal image dataset in diverse environments is essential to effectively train the AI model (Muksit et al., 2022).

In recent years, there has been a growing focus on applying deep learning based visual automation to marine resource management (Nazerdeylami et al., 2021). However, there has been limited work on the AI detection of sea turtles. In 2020, Badawy and Direkoglu collected images from Google and ImageNet (Deng et al., 2009) to create a sea turtle dataset and trained a neural model of Faster R–CNN (Ren et al., 2016) to detect green and loggerhead sea turtles on beaches. They achieved a precision of 95.7% at a threshold of 0.8. Álvarez-Ellacuría et al., (2020) also used deep learning models, specifically Mask R–CNN (He et al., 2017), to detect fish length and understand fish stock dynamics for sustainable management. Additionally, many researchers have applied various deep learning models to automatically detect and classify fishery catches or discards (Malde et al., 2019; French et al., 2020; Tseng and Kuo, 2020; Rick van Essen et al., 2021).

Capturing images of live fish or marine life in their natural habitats presents more challenges than doing so in controlled environments like boats or markets. The vastness of marine and coastal regions, along with the camouflage abilities of many species that allow them to blend with the seabed or surrounding waters, makes data collection for AI training more complex. Although there is a growing accumulation of large-scale coastal marine images for AI training datasets, such as the Deepfish dataset (Saleh et al., 2020) and OzFish (Australian Institute of Marine Science, 2020), compiling these sets requires considerable effort. Despite these advancements, there is still a significant need for building comprehensive training databases. Utilizing metadata from social media and citizen science records can provide valuable supplementary ecological data, especially for marine species that are rare or lack sufficient data (Cranswick et al., 2022).

Little Liuqiu Island in southern Taiwan has a historical reliance on fishing. However, due to the depletion of fishing resources, the island has shifted its focus towards ecotourism, particularly attracting tourists interested in sighting green sea turtles. Conservation initiatives, coupled with pandemic lockdowns, have led to a significant increase in the green sea turtle population in the region. In 2019, there were an estimated 199 wild turtles spotted along the island's coastline, a number that increased to 805 by 2021 (Ocean Conservation Administration, 2021). Nonetheless, the island has experienced a surge in tourism following the easing of Covid-19 restrictions, with the number of visitors more than doubling from 173,307 people to 362,660 people (Liuqiu Township Office). This influx of tourists not only brings economic revenue but has also led to legal cases related to wildlife harassment that could potentially harm the well-being of the green sea turtle population (Coast Guard Director Office). To address these concerns, local communities and government authorities have implemented coastal management measures, including conservation education and ecotourism guidelines, to prevent disturbance of wildlife.

The core concern being addressed revolves around the local community's expectations: how can AI benefit both tourism and the conservation of green sea turtles on Little Liuqiu Island? In this study, our goal is to develop an AI service that can detect green sea turtles in their natural habitat, thereby enriching the sighting experiences for tourists and heightening their conservation awareness. We explore the best training dataset, the optimal AI model, effective evaluation techniques, and practical applications to promote sustainable management of the green sea turtle population.

2. Material and methods

2.1. Study site

Little Liuqiu is a coral island with a surface area of 6.2 km^2, situated approximately 15 km from the southwest coast of Taiwan. The coastline, spanning 12 km, comprises of a reef, sand beaches, and four fishing ports. The Ocean Conservation Administration reports that green sea turtles can be found throughout the island, with the highest frequency of sightings recorded in four areas: Huaping Rock Coast (north), Duozi Bench (northwest), Shanfu fishing port (west), and Lobster Cave (east) (Ocean Conservation Administration, 2021). All four sites were included in this study (Fig. 1).

2.2. AI Model selection and training set up.

The pioneering deep learning algorithm for image recognition, a convolutional neural network (CNN), was introduced by Fukushima in 1980 (Fukushima, 1980). It's essential to clarify that this function is typically employed for images featuring a singular object to avoid ambiguity. Later, Girshick et al. (2014) devised a neural network model for object detection. This model segmented the input image into roughly

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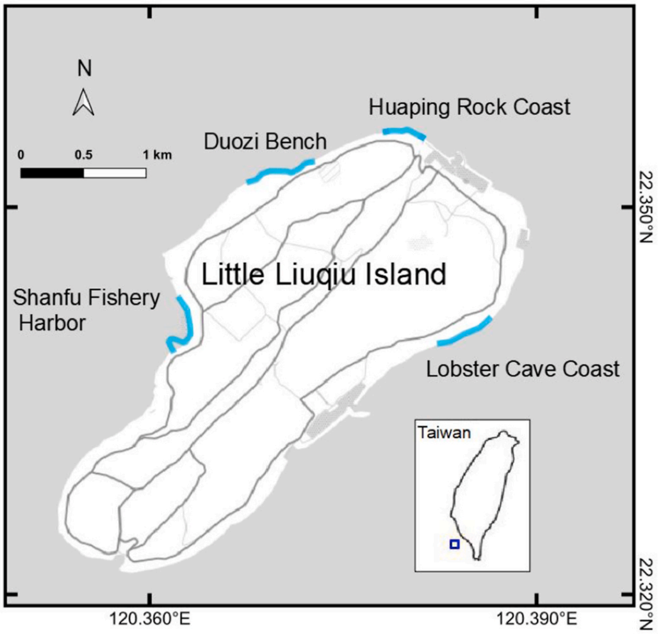


Fig. 1. Study sites around Little Liuqiu Island and the location of the island adjacent to Taiwan (inset).

2000 small regions, then employed a convolutional network to sequentially extract features from each segment. This paved the way for the innovative 'You Only Look Once' (YOLO) model, which partitions the input image into significantly fewer regions (e.g., 7x7 cells). YOLO reframes object detection as a regression challenge, employing spatially distinct bounding boxes associated with class probabilities (Redmon et al., 2016). This approach allows YOLO to predict bounding boxes and class probabilities directly from the input image, streamlining the process. YOLOv3 introduced a novel model architecture with three grid sizes, facilitating the recognition of objects at varying distances and sizes, from proximate to remote and from minuscule to substantial (Redmon and Farhadi, 2018; Guerrieri and Parla, 2021) (Fig. 2). In our research, we juxtaposed the established YOLOv3 model with the more recent YOLOv5s, which boasts a compact architectural design, and the YOLOv5l model, characterized by a more expansive architecture, specifically for detecting wild green sea turtles. The source codes for both YOLOv5s and YOLOv5l can be accessed on GitHub (Glenn, 2022, https://github.com/ultralytics/yolov5). We trained all three models using Linux desktop computers, powered by an RTX3090-24G GPU, with the subsequent hyperparameters: pre-trained weight, training batch size of 32, image dimensions of 800x800, and learning epoch of 200.

2.2. *Image acquisition and annotation*

To assemble our green sea turtle image dataset, we utilized two resources. The first resource was 781 images that we collected between 2016 and 2021 using a UAV (Dji Mavic Pro M1P) or underwater camera (Olympus TG-3). It's important to note that image acquisition was slow until 2019 when the number of sightings increased. The second resource was 681 images obtained from a local islanders' Facebook group named "Turtle Spot Taiwan" (Turtle Spot Taiwan), which was established in 2017. In total, we acquired 1462 images.

In the current study, the sea turtles that appeared in images were treated as objects to be annotated within a bounding box using a labeling program, labeling, the boxes of which were then saved as the ground truth instances (Fig. 3a) encoded as data class (*c*), coordination position (*x, y*) and size (width *w*, height *y*) (Fig. 3b). All training datasets were randomly divided into a training set (80%) and a validation dataset (20%).

2.3. *Evaluation of detection performance of AI models*

The prediction results fell into four scenarios: 1) Success in identifying an actual ground-truth object - true positive (TP); 2) Success in identifying a non-turtle object - true negative (TN); 3) Failure to identify an actual ground-truth object - false negative (FN); and 4) Erroneous identification of non-turtle object as a ground-truth object - false positive (FP).

The precision of the models was calculated using Eq. (1), the recall was calculated using Eq. (2), and the F1-score (the mean value indicating precision and recall) was calculated using Eq. (3):

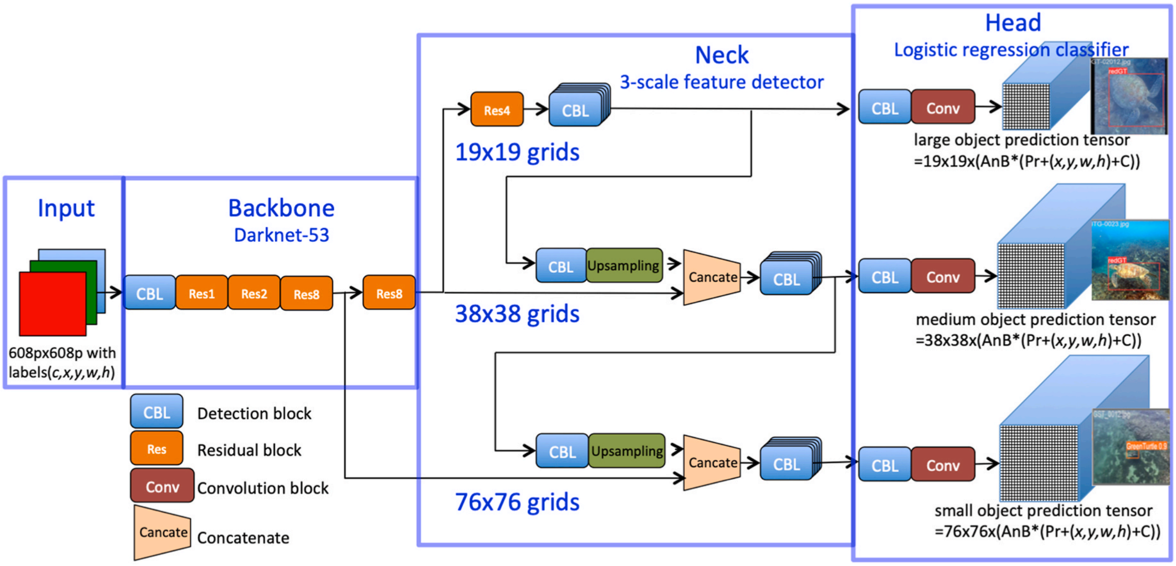
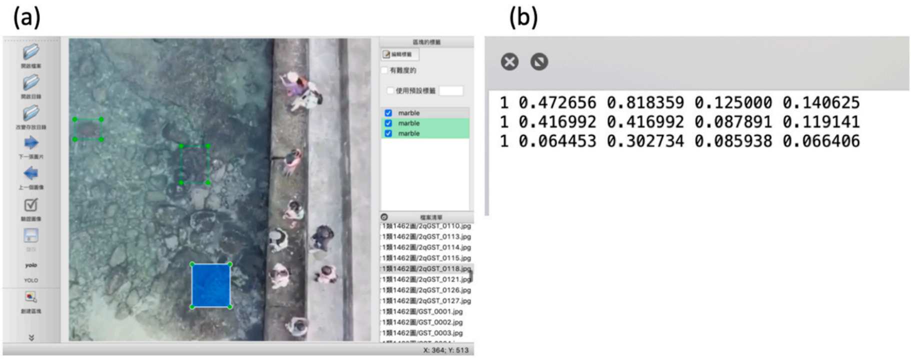


Fig. 2. Architecture and data pipeline stage of YOLOv3. The architecture consists of four main components: "Input," "Backbone," "Neck," and "Head." The "Backbone" component is responsible for performing feature extraction on the input image. The "Neck" component carries out multi-scale feature detection across three scales: 19x19 grids, 38x38 grids, and 76x76 grids. Finally, the "Head" component functions as a logistic regression classifier to predict object labels, positions, bounding sizes, and class probabilities for objects present in the input image.



```
1 0.472656 0.818359 0.125000 0.140625
1 0.416992 0.416992 0.087891 0.119141
1 0.064453 0.302734 0.085938 0.066406
```

Fig. 3. Three instance examples of one object class after labeling via (a) bounding boxes as ground-truth objects; (b) Corresponding coding data, codes created in the form of (*c, x, y, w, h*) after annotation.

$$precision = \frac{TP}{TP + FP} \tag{1}$$

$$recall = \frac{TP}{TP + FN} \tag{2}$$

$$\text{F1 score} = 2 \times \frac{precision \times recall}{prescision + recall} \tag{3}$$

YOLO is meant to detect the class, position, and size of objects. Thus, we also calculated the ratio of area in the predicted bounding box B_p overlapping the area of the actual ground truth box B_g using the intersection of union *IoU* formula, as follows:

$$IOU = \frac{aera\ |B_p \cap B_{gt}|}{aera\ |B_p \cup B_{gt}|} \tag{4}$$

The mAP$_{0.5}$ Eq. (5) measures the averaged precision value of all the cases when *IOU* is 50% threshold area overlap.

$$mAP_{0.5} = \frac{1}{n}\sum_{i=1}^{n} AP_{category\ i} \quad when\ IoU\_threshold = 0.5 \tag{5}$$

While mAP$_{0.5:0.05:0.95}$ Eq. (6) denotes that the mAP from IoU thresholds of 0.5–0.95 in increments of 0.05 is calculated by averaging the Average Precision (AP) at each IoU threshold.

$$mAP_{0.5:0.05:0.95} = \frac{1}{10}\sum_{IoU=0.5}^{0.95} AP_{IoU} \quad when\ IoU\_threshold = 0.5, 0.55, 0.6, 0.65, 0.7, 0.75, 0.8, 0.85, 0.9, 0.95 \tag{6}$$

2.4. AI model optimization experiments

The effectiveness of the AI service depends on the optimization of the AI model and the training dataset. In this study, we assess how the size and composition of the training dataset affect the detection performance of different YOLO models. Our goal is to identify the most efficient AI models for system in green sea turtle management.

2.4.1. Experiments of training data volume

YOLOv3, YOLOv5s and YOLOv5l models were trained using two datasets (single-class) with different volumes and then assessed in terms of precision, recall, and F1-score value. The first training dataset included 781 images collected during studies, whereas the second dataset included the same images plus 681 additional images bringing the total to 1462.

2.4.2. Experiments of data class classification and instance amount

The impact of data classification and instance quantity on identification performance was evaluated by annotating the objects/instances in the original dataset images as a single class. The same dataset images were then re-annotated as two and three classes using the same settings to determine how the volume and quality of annotated classes affected accuracy mAP$_{0.5}$. The accuracy of each class at different class settings was evaluated, and comparisons were made between them.

2.4.3. Evaluation of overall detection performance of the various YOLO models

We evaluated overall object detection performance of YOLOv3, v5s and v5l when applied to the green sea turtle datasets in terms of F1-score (harmonic mean between precision and recall), mean average precision of object detection (mAP$_{0.5}$ and mAP$_{0.5:0.05:0.95}$).

2.5. Deployment of trained AI model to execute service

Once the AI model has been trained, it will be deployed on a publicly accessible server, enabling continuous green sea turtle detection services via the Internet. With this deployment, our AI service becomes fully operational and accessible to the public. The work breakdown structure of this study is divided into four distinct blocks: 1). data collection, 2). training AI, 3). online deployment of the trained AI, and 4). facilitating user interaction with the service system (as illustrated in Fig. 4).

3. Results

3.1. Evaluation on training dataset volume effect

In our examination of single-class annotations focused solely on green sea turtle detection, we evaluated the performance of three models: YOLOv3, YOLOv5s, and YOLOv5l, with respect to dataset size. We tested these models using both a smaller dataset comprising 781 images and a larger one with 1462 images. Their efficiency was gauged using precision, recall, and F1-score metrics. The findings indicated that,

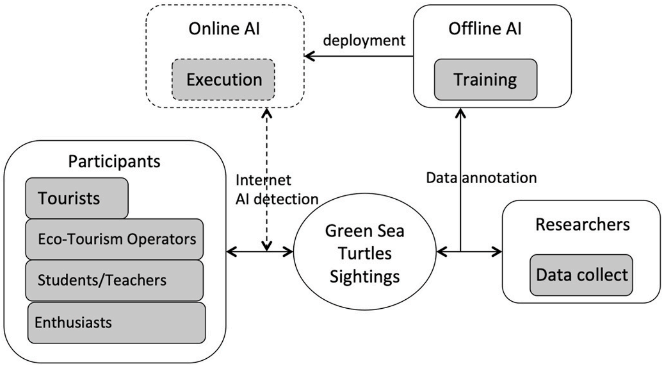


Fig. 4. The work breakdown structure and information flow of the AI service for coastal green sea turtle management. The dotted lines represent the flow of information via the Internet.

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with the smaller dataset, YOLOv3 outperformed the others across all three metrics. YOLOv5s exhibited superior results in terms of precision and F1-score, while YOLOv5l lagged behind in all three metrics when trained on the smaller dataset (Table 1).

3.2. *Analysis of annotation results*

In their research on green sea turtle populations in the Atlantic and Gulf of Mexico, Witherington and Witherington (2015) observed intriguing variations in the color patterns of the carapace. Juvenile (3–10 years old) and subadult (10–30 years old) turtles tend to exhibit vibrant red radiating streaks on the scutes (Fig. 5a), whereas adults (over 30 years old) exhibit a noisy scattering of colors (Fig. 5b). In the current study, we observed two distinctive patterns on the carapace of green sea turtles around Little Liquid Island. One pattern was “light to dark brown shading with dark mottling” which we classified as marbleGT/elder (Fig. 5b), due to the fact that these characteristics are generally observed in adult animals (>30 years). The other pattern was “red with brown radial features” (Fig. 5a), which we classified as “redGT/young”. We determined that most of the animals with the red radial pattern were smaller with keels on the rear of the carapace, both of which are characteristic of young turtles (<30 years). Many of the carapace patterns were not easily recognizable in the following situations: 1) when viewed as small, distant objects from the drone (Figs. 5c), 2) when they appeared to blend in with the water surface when viewed from the sea bank (Figs. 5d), and 3) when the patterns became invisible when lit from behind or only the body parts of the animal were visible (Fig. 5e). These images were broadly classified as “GreenTurtle” (Fig. 5c, d, e). The amount of annotated instances of each class in two datasets is showed at Table 2.

The results for all annotation of training datasets were visualized in terms of instance structure, based on normalized position coordinates (x, y) and width to height ratio (w, h) to determine the shape of the bounding box (square or rectangle). Most of the instances were close to the center of the images and most of the instances were vertical rectangles with a roughly equal distribution of sizes applicable to the three sizes (i.e., small, medium, and large) (Fig. 6). Imbalances in instance distribution can hinder the training of the neural network model (Zhang et al., 2021). The distribution of classes in the larger dataset was more balanced (Fig. 6e) than that in the smaller dataset, in which the number of redGT instances (481) was nearly double that of marbleGT (212) (Fig. 6b). The use of three-class annotation greatly improved the balance of amount, wherein number of GreenTurtle instances exceeded the redGT and marbleGT instances by roughly 30% at two-class case (Fig. 6c and f).

3.3. *Learning trajectory and trained weights*

All three models (YOLOv3, YOLOv5s, YOLOv5l) were trained using 200 epochs, each of which involves the one-time use of all training and validating data in a given dataset. The learning efficiency and number of required epochs were determined by assessing the precision, recall, mAP$_{0.5:0.05:0.95}$, and mAP$_{0.5}$. The number of training epochs was proportional to the number of calculations and training time. YOLOv3 presented a steep (fast) learning slope, reaching convergence after 50 epochs (Fig. 7a, b, c). Lightweight (fewer layers) YOLOv5s required roughly 100 epochs to reach convergence (Fig. 7d, e, f). Heavyweight (more layers) YOLOv5l required more than 100 epochs to reach convergence (Fig. 7g, h, i).

After training, the models identify and learn from the patterns in the training dataset images. The outcomes of this learning process are the trained weights, which are later utilized to execute their designated functions. In our experiments, the sizes of the trained weights for YOLOv3, YOLOv5s, and YOLOv5l are 246.3 MB, 14.8 MB, and 93.6 MB, respectively.

3.4. *Class setting and instance volume effects*

The configuration settings of a neural network model can profoundly influence its detection capabilities for various object types. In our experiments, we evaluated the model’s performance by categorizing a single dataset into multiple classes, subsequently analyzing the impact of increasing instance volumes within consistent class settings. Results demonstrated a steady positive correlation between increasing instance volume and class accuracy mAP$_{0.5}$ scores solely for YOLOv5l, whereas the other two models exhibited variable trends. Intriguingly, in the two-class and three-class configurations, increasing the instance volume generally had a negative effect on the class mAP$_{0.5}$ scores for both YOLOv3 and YOLOv5s. A notable exception was observed when the instance volume of the marbleGT/elder_2 class was augmented from 212 to 609 instances, leading to a surge in the class mAP$_{0.5}$ scores (as illustrated in Table 3).

After accounting for variations in instance volume and model types, and by averaging all mAP$_{0.5}$ values for analogous classes, the GreenTurtle_1 class emerged with the top average class mAP$_{0.5}$ at 98.6%. It was followed by the redGT/young_2 class with 94.6% and the marbleGT/elder_2 class at 93.9%. A similar trend was discerned in the three-class configuration, with mAP$_{0.5}$ values registering 88.8% for the redGT/young_3 class and 86.2% for the marbleGT/elder_3 class. Overall, an inverse relationship was evident between the average class mAP$_{0.5}$ and the diversity of class configurations. Yet, the GreenTurtle_3 class still managed to secure an impressive average class mAP$_{0.5}$ of 97.2%, the second highest across all classes, even with its instance volume being relatively much smaller than several other classes (refer to Table 3).

3.5. *Comparative analysis of YOLO model performance*

In our analysis, we identified a general positive correlation between the quantity of training instances and the validation performance metrics across all three models, specifically for the F1-score (Fig. 8b), mAP$_{0.5}$ (Fig. 8c), and mAP$_{0.5:0.05:0.95}$ (Fig. 8d). Examining the F1-score performance of the trio, YOLOv3 and YOLOv5s consistently outperformed YOLOv5l, particularly in terms of instance volume per class. These two models, YOLOv3 and YOLOv5s, showcased comparable outcomes across the board, outshining YOLOv5l in all key performance metrics: F1-score (Fig. 8b), mAP$_{0.5}$ (Fig. 8c), and mAP$_{0.5:0.05:0.95}$ (Fig. 8d). To provide a holistic view of the models’ efficacy, given that their relative performances were contingent on specific training dataset parameters, we amalgamated the results from all performance indicators across experiments (Fig. 8). In the context of green sea turtle detection, YOLOv5s emerged as the most proficient model (Fig. 9).

Table 1

Performance of YOLOv3, YOLOv5s, and YOLOv5l as a function of dataset volume in terms of precision, recall, and F1-score.

	YOLOv3			YOLOv5s			YOLOv5l		
	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
781image	98.25%	97.68%	97.96%	98.72%	97.10%	97.90%	95.58%	95.37%	95.47%
1462image	96.90%	97.50%	97.19%	97.21%	97.82%	97.51%	95.71%	97.47%	96.58%

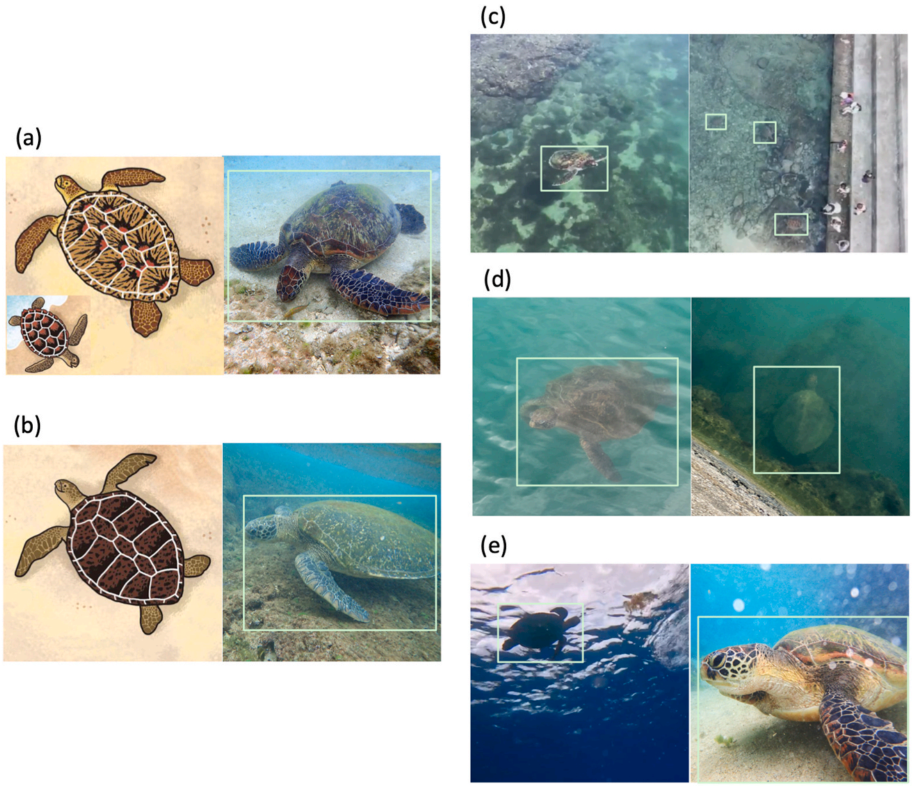

Fig. 5. Feature patterns used for annotating label classes: (a) redGT/young patterns indicative of juvenile or subadult; (b) marbleGT/older pattern indicative of adult (>30 years); (c) Images from UAV drone; (d) Turtles obscured by murky water and surface reflections hindering identification; (e) Backlight and turtle's body part.

Table 2
Number of instances of each class in the two training datasets after annotation.

Dataset images	Class	Labeling names and instances numbers		
		GreenTurtle	redGT/young	marbleGT/elder
781image	1	685	NA	NA
	2	NA	481	212
	3	279	202	221
1462image	1	1287	NA	NA
	2	NA	678	609
	3	417	502	368

Here is 80% instances in training dataset.

3.6. AI service deployment

The AI detection service utilizing the YOLOv5s model, trained on a compact dataset comprising two classes, is now available online for both local tour guides and tourists. This initiative seeks to engage tourists actively in monitoring and identifying turtles as they journey along the island's shores. The service provides a user-centric application interface, API (Fig. 10a), optimized for diverse mobile devices, facilitating straightforward photo uploads for AI identification (Fig. 10b). Whenever there's an active Internet connection, the results are swiftly delivered to the user through the same API (Fig. 10c).

4. Discussions

4.1. Effects of quantities and contents of training dataset

The fact that YOLO are based on deep learning means that detection performance depends not only on the neural network architecture but also on the training dataset. Many previous attempts to automate the detection and identification of marine organism focused entirely on the neural model with little consideration for the training dataset (Salman et al., 2020; Zhao et al., 2021; Muksit et al., 2022). When we started this research, we were unsure about the quantity of images required to train a highly accurate AI model. We could only assume that the more appropriate green sea turtle images we had, the better. After three years of field collection, we sorted out 782 images that seemed suitable for AI training. We later added another 682 images from the social media platform "Turtle Spot Taiwan", increasing the photo count by nearly 47%. This addition improved the three performance indicators (precision, recall, and F1-score) for the YOLOv5l model by about 1%. For YOLOv5s, only the recall value increased, whereas, for YOLOv3, the performance decreased across the board (as shown in Table 1). For a single object class, over 700 training images can evidently achieve a satisfactory precision and recall rate of above 97% for both YOLOv3 and YOLOv5s. To our knowledge, turtle image recognition has only been done by Badawy and Direkoglu (2020), who used about 500 turtle photos from open-source online databases to train the Faster R–CNN model and achieved a precision of 95.7%.

The F1-score of YOLOv3's performance in our study stands out when compared with other marine training datasets. Saleh et al. (2020) utilized the expansive OzFish database (Australian Institute of Marine Science, 2020) comprising 1800 images with 43k instances and achieved an F1-score of 72%. When applying YOLOv3 to their own DeepFish dataset, which contains 4505 images with 15k instances, they reached an F1-score of 94%. In contrast, our research used a larger dataset of 1462 images and 1608 instances, achieving an F1-score of 97.19% (Table 1). Remarkably, even with our smaller dataset of 782 images and 856 instances, we attained an F1-score of 97.96%. These findings suggest that model performance is influenced not just by the sheer quantity of data, but also potentially by the quality and content of the dataset.

To investigate the influence of dataset instance volume, we conducted experiments with varied annotated class compositions. In a general trend, the detection accuracy, denoted by $\text{mAP}_{0.5}$, for each class shows a positive correlation with its instance volume, especially for

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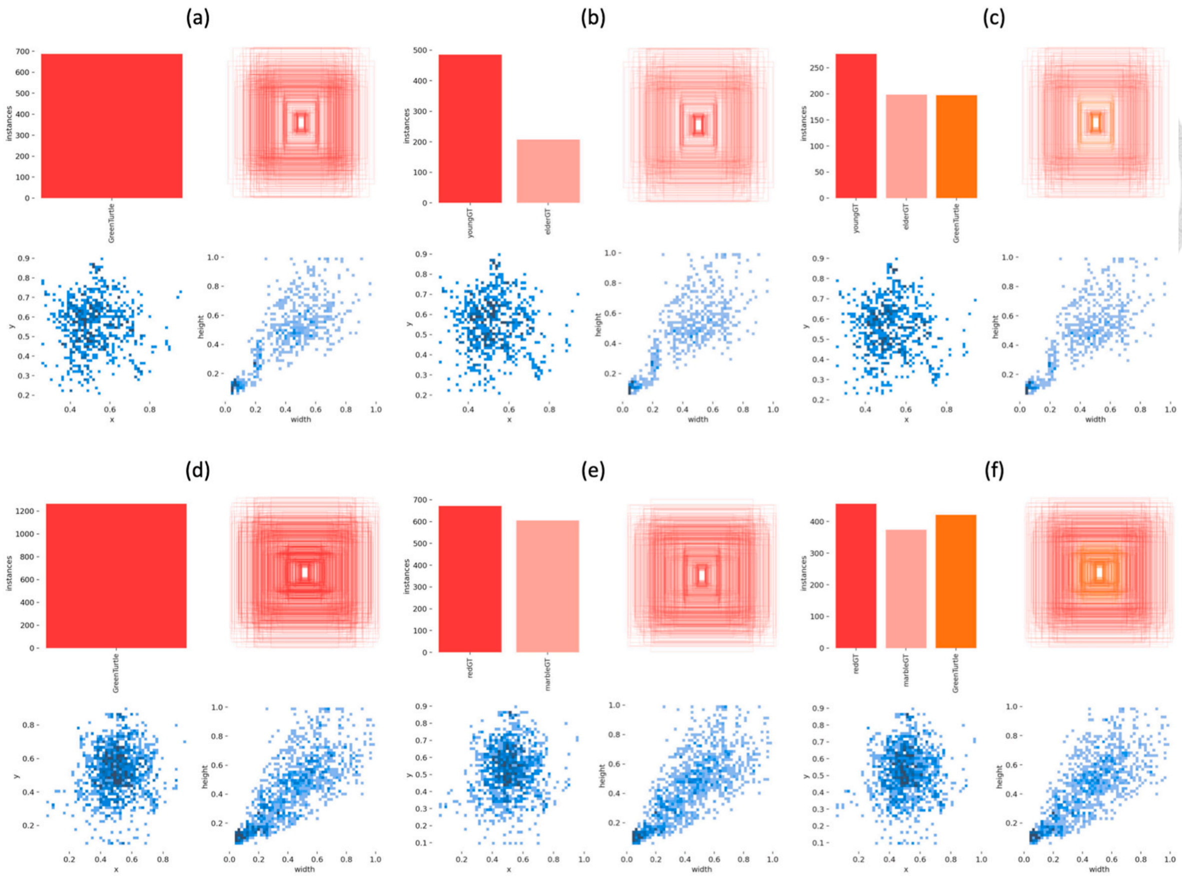


Fig. 6. Structure map of instances of two classes setting: the number of instances, bounding box shape, bounding box size, and bounding box position. (a) Small dataset/single-class; (b) Small dataset/two-classes; (c) Small dataset/three-classes; (d) Large dataset/single-class; (b) Large dataset/two-classes; (c) Large dataset/three-classes.

YOLOv5l. However, this trend is not consistently observed for the other two models. Notably, in the three-class setting, the $mAP_{0.5}$ for the GreenTurtle_3 class is significantly higher than the other two classes, despite its lower instance count of 221 (Table 3). This discrepancy may stem from the diverse range of object sizes present in this class, spanning from large objects (e.g., close-up views of body parts) to small objects (e.g., aerial shots taken by drones) (Fig. 5c, d, e). This research underscores that a dataset encompassing a broad spectrum of object sizes can significantly elevate detection accuracy ($mAP_{0.5}$) compared to datasets with uniformly sized objects. This enhanced performance can be linked to the design philosophy behind YOLOv3 and its subsequent variants. Unlike R–CNN (Girshick, 2015), which primarily recognizes 2D planar patterns, YOLOv3 and its subsequent variants also accounts for dimensions influenced by the object's distance from the camera (Fig. 2) (Redmon and Farhadi, 2018).

4.2. *Comparison of learning, computation speed and performance efficiency*

Neural network learning is an iterative trial-and-error process that continues until the network reaches convergence, which corresponds to achieving the minimum error and the highest learning scores. Our experiments demonstrated that the final converged F1-score and $mAP_{0.5}$ scores can serve as indicators of dataset content, while the learning trajectories within 200 epochs can provide insights into the learning process and efficiency of different model designs with a specific dataset. Notably, we observed that the learning trajectory of YOLOv5l exhibited more fluctuations and converged at a slower rate to the maximum learning scores compared to the learning trajectories of YOLOv3 and YOLOv5s (Fig. 7). Overfitting occurs when a model learns the training data too well, to the point where it performs poorly on unseen data due to failure in capturing the true underlying process. The notion that increasing the number of training epochs invariably leads to overfitting in deep learning models is contentious (Afag and Rao, 2020; Bejani and Ghatee, 2021). Our study's scope is limited in determining whether the overfitting phenomenon has impacted the models we trained.

YOLO is a dynamic open framework, evolving as a neural network that is primed for continual enhancement. Studies utilizing the MS COCO dataset (Lin, 2014) have conclusively shown that subsequent versions of YOLO outperform their predecessors in terms of speed and accuracy (Jiang et al., 2022; Wang et al., 2022). Consequently, YOLOv5l and YOLOv5s are anticipated to surpass YOLOv3 in accuracy. YOLOv5s, a streamlined version of the YOLOv5 model, is optimized for speed and efficiency at the sacrifice of some accuracy, making it ideal for devices with constrained computational capacities or for real-time applications. Conversely, YOLOv5l, a more extensive variant of the YOLOv5 model, is tailored to deliver superior accuracy, albeit requiring more computational resources.

Contrary to expectations, our experimental findings showed that YOLOv3 surpassed YOLOv5l in terms of accuracy. Notably, despite its compact design, YOLOv5s demonstrated superior performance compared to the more intricate, densely-layered design of YOLOv5l when applied to a small-scale dataset. While the detection performance on the MS COCO dataset ranked YOLOv5l > YOLOv5s > YOLOv3, our specific case yielded a ranking of YOLOv5s > YOLOv3 > YOLOv5l (Fig. 9). Mahmood et al. (2020) investigation into YOLOv3 revealed that supplementing with a moderate number of synthetic images (e.g., 100, 250, or 500) to account for object occlusion enhanced mAP values.

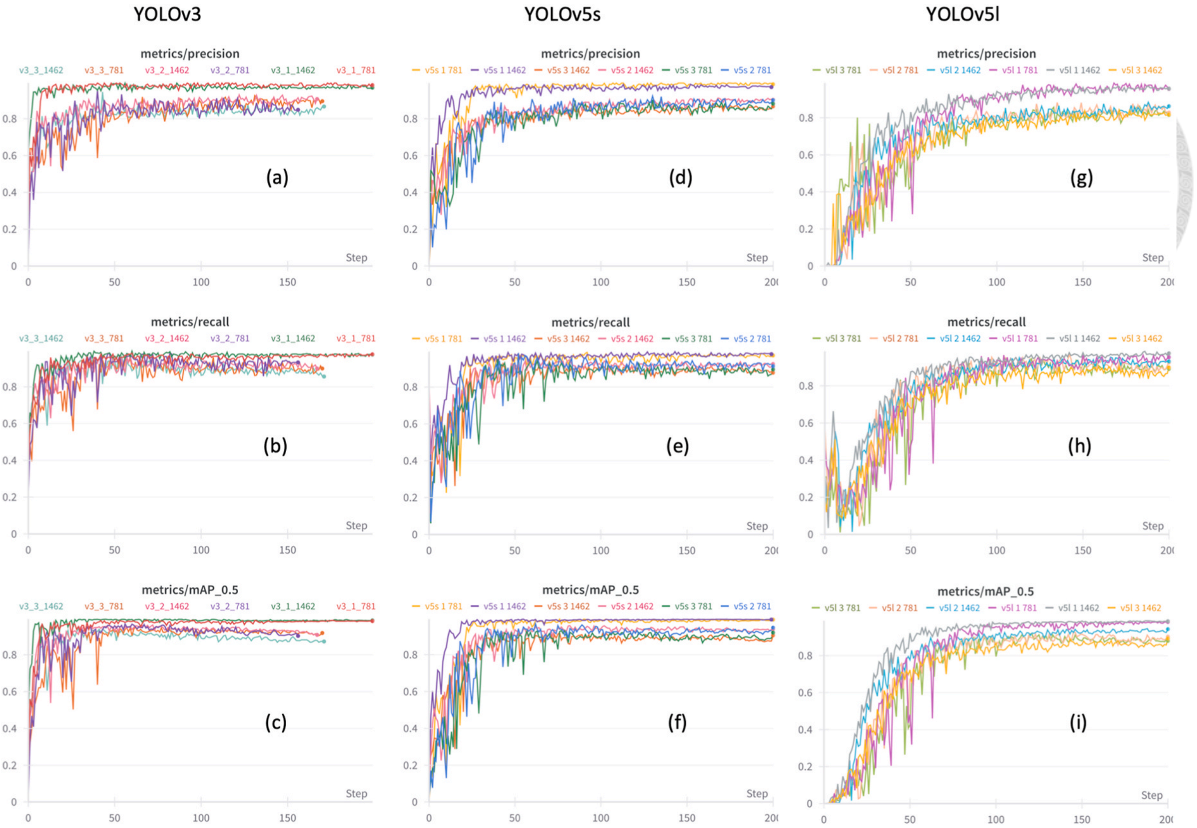


Fig. 7. Learning trajectory as a function of dataset parameters: YOLOv3 (a) Precision; (b) Recall; (c) $mAP_{0.5}$; YOLOv5s (d) Precision; (e) Recall; (f) $mAP_{0.5}$; and YOLOv5l (g) Precision; (h) Recall; (i) $mAP_{0.5}$.

However, introducing an excessive number (e.g., 500) of synthetic images led to diminished $mAP_{0.5}$ values. Our results mirrored this trend, indicating that both YOLOv3 and YOLOv5s yielded superior F1-score (Table 1) and class $mAP_{0.5}$ performance (Table 3) when trained on less voluminous datasets. The discrepancy in performance could be attributed to the nature of the training datasets. The MS COCO dataset is an expansive collection comprising 330K images and 1.5 million instances, predominantly sourced from general daily-life images. In contrast, our dataset specifically captures sightings of wild green sea turtles at Little Liuqiu Island. Additionally, the trained weights based on our two datasets were YOLOv5s (14.8 MB), YOLOv5l (93.6 MB), and YOLOv3 (246.3 MB). A reduced trained weight indicates fewer computational parameters, ensuring efficient hardware and energy usage during calculations. Balancing performance accuracy and efficiency, we have chosen YOLOv5s for deployment in our online AI service.

4.3. AI service and user experience

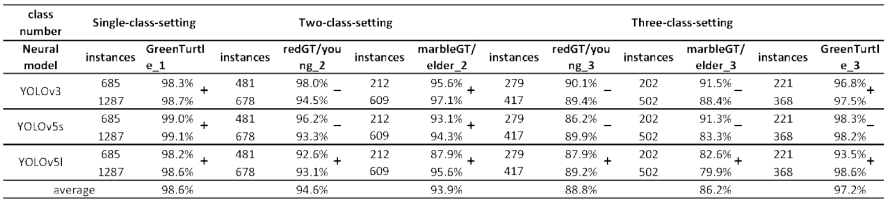
Real-time information on sea turtle sightings along the island's coastline is indispensable for tourist operators conducting ecotourism and instructors overseeing environmental education programs. Our AI service, optimized for real-time use, provides tourists with an enhanced coastal exploration experience. By utilizing their smartphones, tourists can capture images of green sea turtles along the shoreline and instantly receive identification results from the AI detection service. This service is built on the YOLOv5s model, trained on a specialized two-class dataset, and boasts an impressive class $mAP_{0.5}$ of 96.2% and 93.1%. Remarkably, it can discern between the young red-patterned and the older marble-patterned green sea turtles.

Such immediate, in-situ identification enriches the experience of first-time visitors and users, making encounters with sea turtles in their natural setting all the more memorable. Beyond simple identification, the ability of the AI service to differentiate between younger and older sea turtles provides users with a deeper, more informative interaction, elevating their overall experience.

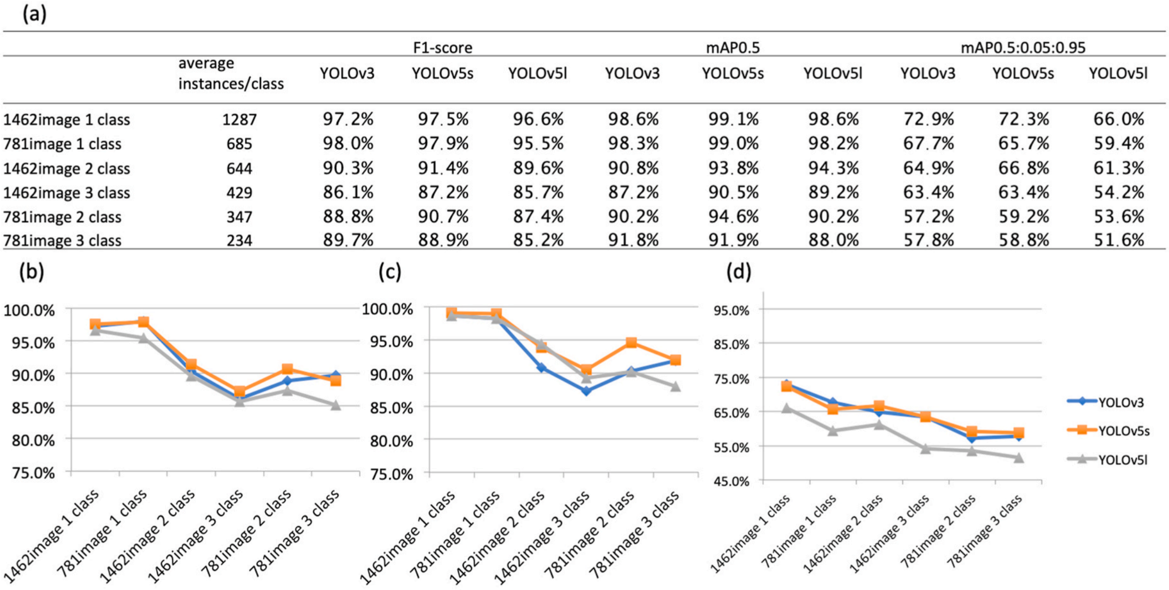
Tour operators can capitalize on this digital service to tailor educational and tour agendas, motivating visitors to actively engage in observing the green sea turtle community. Once tourists snap pictures of wild, free-roaming green sea turtles that are subsequently identified and annotated by the AI system, they can broadcast these images on their personal social media platforms. Such shared experiences not only amplify their personal digital travel journey but also bolster the promotion of green sea turtle ecotourism (Lamb, 2019). While in pursuit of capturing these moments, tourists are naturally deterred from activities that might startle or deter the sea turtles. This promotes conservation education objectives and alleviates the strain on wildlife protection enforcement.

AI-powered automation systems, commonly used in marine environments for tasks such as monitoring catch or discard ~~species~~specimens, often rely on fixed cameras. These setups facilitate a side-by-side comparison of AI model performance with human observations (van Helmond et al., 2017; Álvarez-Ellacuría et al., 2020; van Essen et al., 2021). However, the task of comparing our AI model's precision to human evaluations becomes complex, particularly when the platform is open to the public. This AI service further constrains our oversight of user-submitted imagery. Still, we can track the outputs at the server-side. Notably, several submissions included cartoons and mural artworks that our system incorrectly identified as genuine green sea turtles (Fig. 10d). Such erroneous outputs are termed "AI hallucinations", scenarios where AI systems generate realistic but incorrect or fictive results (Goodfellow et al., 2015). Conversely, certain users purposely uploaded inappropriate images, aiming to challenge the AI's detection capabilities, highlighting their intrigue in AI's detective

Table 3
The instance $mAP_{0.5}$ scores and average class $mAP_{0.5}$ scores of various YOLO models as a function of class annotation settings. The plus and minus symbols indicate an increase or decrease in the $mAP_{0.5}$ scores when the number of instances was added.



class number	Single-class-setting			Two-class-setting						Three-class-setting								
Neural model	instances	GreenTurtle_1		instances	redGT/young_2		instances	marbleGT/elder_2		instances	redGT/young_3		instances	marbleGT/elder_3		instances	GreenTurtle_3	
YOLOv3	685	98.3%	+	481	98.0%	−	212	95.6%	+	279	90.1%	−	202	91.5%	−	221	96.8%	+
	1287	98.7%		678	94.5%		609	97.1%		417	89.4%		502	88.4%		368	97.5%	
YOLOv5s	685	99.0%	+	481	96.2%	−	212	93.1%	+	279	86.2%	−	202	91.3%	−	221	98.3%	−
	1287	99.1%		678	93.3%		609	94.3%		417	89.9%		502	83.3%		368	98.2%	
YOLOv5l	685	98.2%	+	481	92.6%	+	212	87.9%	+	279	87.9%	+	202	82.6%	+	221	93.5%	+
	1287	98.6%		678	93.1%		609	95.6%		417	89.2%		502	79.9%		368	98.6%	
average		98.6%			94.6%			93.9%			88.8%			86.2%			97.2%	



(a)

		F1-score			mAP0.5			mAP0.5:0.05:0.95		
	average instances/class	YOLOv3	YOLOv5s	YOLOv5l	YOLOv3	YOLOv5s	YOLOv5l	YOLOv3	YOLOv5s	YOLOv5l
1462image 1 class	1287	97.2%	97.5%	96.6%	98.6%	99.1%	98.6%	72.9%	72.3%	66.0%
781image 1 class	685	98.0%	97.9%	95.5%	98.3%	99.0%	98.2%	67.7%	65.7%	59.4%
1462image 2 class	644	90.3%	91.4%	89.6%	90.8%	93.8%	94.3%	64.9%	66.8%	61.3%
1462image 3 class	429	86.1%	87.2%	85.7%	87.2%	90.5%	89.2%	63.4%	63.4%	54.2%
781image 2 class	347	88.8%	90.7%	87.4%	90.2%	94.6%	90.2%	57.2%	59.2%	53.6%
781image 3 class	234	89.7%	88.9%	85.2%	91.8%	91.9%	88.0%	57.8%	58.8%	51.6%

Fig. 8. Performance indicators for all experiment scenarios in this study: (a) Performance comparison of YOLOv3, YOLOv5s, and YOLOv5l; (b) F1-score, (c) $mAP_{0.5}$, and (d) $mAP_{0.5:0.05:0.95}$.

potential. From a user experience perspective, pinpointing entities that resemble sea turtles, albeit mistakenly, trumps a non-responsive system. Importantly, upon manual annotation, these user-contributed images evolve into invaluable assets for refining future AI model training and accuracy. Additionally, these user submissions offer a treasure trove of insights into human-green sea turtle interactions, encapsulating details like capture timestamps and GPS coordinates. Such data could potentially uncover the temporal and spatial distribution patterns of the green sea turtle population, warranting further exploration and research.

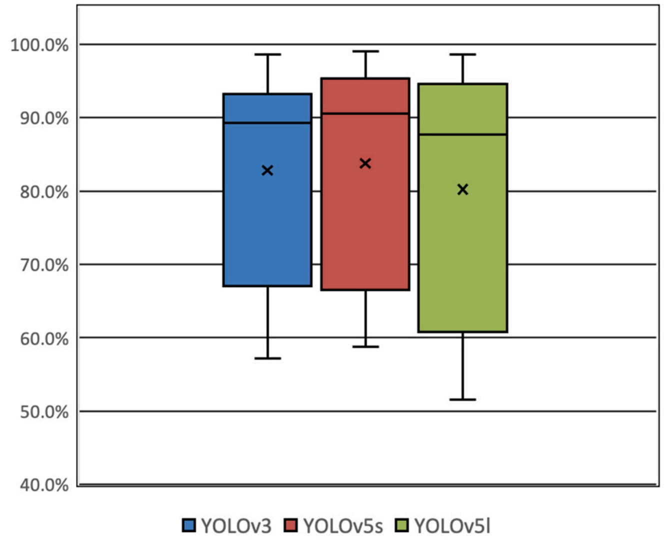


Fig. 9. Boxplot of F1-score, $mAP_{0.5}$, and $mAP_{0.5:0.05:0.95}$ based on all experiment results using YOLOv3, YOLOv5s, and YOLOv5l.

4.4. *Conservation implications*

Our study demonstrates the significant impact of integrating AI deep learning, particularly the YOLOv5s model for real-time image recognition, in marine conservation efforts. By utilizing this technology, we transform tourists from passive observers into active participants in conservation. The implications of this engagement are threefold.

(1). Educational Impact: The AI service enables tourists to identify and learn about green sea turtles in their natural habitat. This interactive experience not only educates but also increases awareness, fostering a deeper appreciation for marine life. We contend that such informed and engaged tourists are more likely to support and actively contribute to conservation initiatives.

(2). Behavioral Change: Our approach promotes a non-intrusive way to interact with marine life, aiming to curb harmful tourist behaviors like touching or chasing turtles, which can cause stress and injury to these creatures. By encouraging more responsible ecotourism practices, we aim to reduce the negative impact on marine wildlife.

(3). Data Collection and Monitoring: Tourist-captured photographs serve a dual purpose: enhancing the visitor experience and contributing to a valuable database of turtle sightings. This crowdsourced approach aids in monitoring turtle populations' health and distribution, offering essential insights for both conservationists and researchers.

In short, leveraging advanced technology in this manner not only enriches the tourist experience but also plays a crucial role in the broader context of marine conservation.

5. Conclusions

In this research, we pioneered a green sea turtle conservation approach for tourists by integrating AI object detection algorithms. Our comprehensive methodology spanned from field image collection and AI training to the evaluation of three YOLO neural models (YOLOv3, YOLOv5s, YOLOv5l), culminating in the system's practical deployment. We discerned that the model training outcomes were markedly shaped by both the volume and the diversity of the training images. While a dataset exceeding 220 varied images typically yielded promising results, a disproportionately extensive dataset with redundant content might inadvertently compromise the neural model's efficacy. It's pivotal to understand that for YOLO models, merely adopting a recent version or a model with augmented neural layers, especially with a limited training dataset, doesn't unequivocally translate to enhanced performance. Rather, the detection efficacy is intrinsically linked to the representation of various object sizes in the images, encompassing small, medium, and large specimens. Given its broad applicability, our research paradigm, centered on refining AI training datasets and algorithms for green sea turtle detection, promises immense potential for conserving marine turtles.

Our study reveals that smaller datasets with high diversity in representations—capturing various angles, environment conditions, and scales—can be more effective for training robust models than merely larger data volumes. This is particularly pertinent for management bodies with resource constraints, as it suggests that investing in quality and diversity of data, rather than quantity, leads to cost-effective and feasible data collection strategies. This finding is invaluable for ecological and conservation efforts, guiding managerial bodies to

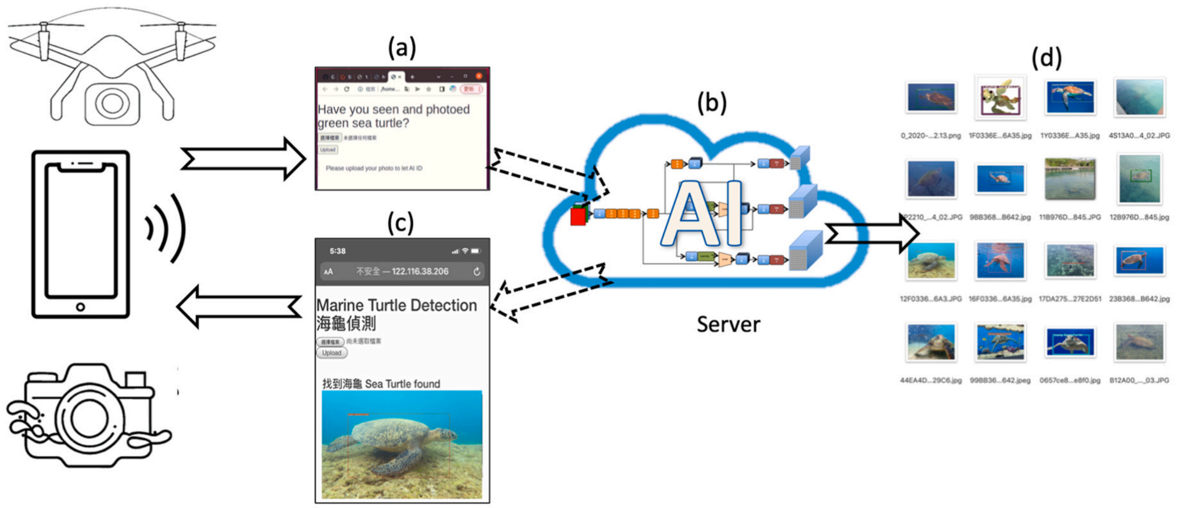


Fig. 10. The architecture and information flow of AI detection service for green sea turtles detection. (a) Images are sent as queries via user interface API, (b) then upload to AI neural model for green sea turtle detection. (c) Identification results are sent back to users through user interface API, and all queries and results are stored on servers, (d) examples of detected images uploaded by various users.

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develop efficient AI tools that are effective even with the challenges and expenses associated with extensive data gathering in marine biology.

CRediT authorship contribution statement

Vincent Y. Chen: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ya-Wen Wu:** Data curation. **Chih-Wei Hu:** Software, Data curation. **Yu-San Han:** Supervision, Resources, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Article

Hybrid Intelligence for Marine Biodiversity: Integrating Citizen Science with AI for Enhanced Intertidal Conservation Efforts at Cape Santiago, Taiwan

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Abstract: Marine biodiversity underpins the formation of marine protected areas (MPAs), necessitating detailed surveys to account for the dynamic temporal and spatial distribution of species influenced by tidal patterns and microhabitats. The reef rock intertidal zones adjacent to urban centers, such as Taiwan's Cape Santiago, exhibit significant biodiversity, yet they are increasingly threatened by tourism-related activities. This study introduces an artificial intelligence (AI)-empowered citizen science (CS) approach within the local community to address these challenges. By integrating CS with AI, we establish a hybrid intelligence (HI) system that conducts in situ biological surveys and educational programs focused on reef ecological conservation. This initiative not only facilitates the collective gathering and AI-assisted analysis of critical data but also uses machine-learning outputs to gauge data quality, thus informing subsequent data collection and refinement strategies. The resulting collectivity and iterative enhancement foster a mutual and continuous HI learning environment. Our HI model proves instrumental in fostering community engagement and public involvement in CS endeavors, cultivating the skills necessary for documenting rocky intertidal biodiversity shifts. These efforts are pivotal for informing the design and governance of future MPAs, ensuring their efficacy and sustainability in marine conservation.

Keywords: marine protect areas; rocky intertidal ecosystem; hybrid intelligence; citizen science; artificial intelligence

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1. Introduction

Coastal regions, including the marine littoral zone, are biological powerhouses [1]. They offer refuge to an expansive array of marine life and directly benefit humanity in multifarious ways [2]. From food sources and economic avenues to recreational pursuits and the conservation of cultural heritages, these ecosystems are indispensable [3]. In parallel, rocky intertidal systems, especially those adjacent to urban locales, are paramount to sustaining ecological balances while also being focal points for economic, social, and recreational engagements [4].

However, the allure of these regions is both their strength and vulnerability. The recent upsurge in coastal tourism and its resultant economic windfall for local regions [5,6] draw legions of tourists. Urban inhabitants, especially, are enchanted by the serene coastal landscapes [7] and the prospect of close encounters with marine fauna. Yet, this very attraction coupled with activities like marine organism harvesting and heedless trampling cast shadows of environmental stress on these habitats [8–10]. The rich biodiversity, a hallmark of these zones, faces relentless challenges. Rocky intertidal areas, rife with microhabitats, stand as evidence of this. The seemingly benign acts of visitors, such as

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walking over tide pools or curiously overturning rocks, inflict lasting ecological scars. The cascading effects of such disturbances manifest in dwindling algal populations, impacting both fleshy and coralline types [11], and in the perceptible strain on marine entities, like echinoderms [12], mollusks [13,14], and crustaceans [15].

The Anthropocene epoch, marked by significant human impact on the Earth's biophysical systems, has led to intensified pressures on coastal regions due to population growth, urbanization, and climate change [16]. This has notably affected rocky intertidal ecosystems with human interaction evolving from fishery exploitation to recreational activities like adventure tourism [17]. A multifaceted coastal management approach, incorporating diverse strategies from legal to educational, is essential to mitigate environmental impacts and encourage societal participation [18]. Additionally, the largely unexplored marine domain presents opportunities for marine citizen science (MCS). MCS plays a crucial role in filling research gaps and enhancing global marine conservation efforts [19,20]. It provides cost-effective, robust data that inform policy decisions [21,22] while increasing public science literacy and community engagement in marine issues [23–25] from cetacean conservation [26,27] to addressing plastic pollution [28], thereby enabling community-driven initiatives to transform research into effective policies [29,30].

At the heart of this movement is the citizen science (CS) research methodology that enlists the general public in data collection, categorization, or scientific analysis [31]. Historically, it has been instrumental in various marine research undertakings. Notable projects include monitoring reef fish ecosystems [32], tracking queen conch species populations [33], discerning seagrass bed dynamics [34], and mapping the distribution patterns of marine litter [35,36]. The unique advantage of CS in marine projects lies in its capacity to amplify the spatial and temporal scope of studies [37,38].

Yet, the integration of projects/research with CS is not without challenges. Concerns often center on the data quality when gathered by non-professionals, especially for intricate biodiversity datasets, which could potentially impede their application [39]. Nevertheless, recent innovations offer solutions. As highlighted by Earp et al. [40], implementing stringent protocols, ensuring thorough training, and adhering to meticulous data verification processes can elevate the data's quality. With such measures in place, data sourced from citizen scientists can rival if not match those procured by their professional counterparts, as evidenced in their intertidal algae ecology experiment.

AI has been employed to augment and enhance human understanding of the environment, including perceptions of citizen scientists [41]. While CS and AI are often viewed as separate tools for ecological monitoring, recent studies indicate that a symbiotic relationship between human intelligence and AI, termed hybrid intelligence (HI) [42,43], can strategically unite the two, enhancing outcomes for conservation activities. By pairing the public engagement benefits of CS projects with the sophisticated analytical prowess of AI, there is the potential to foster greater multi-stakeholder consensus on matters of public [44] and scientific importance. Moreover, the integration of both methodologies can expedite data collection and processing relative to traditional scientific approaches, indicating a promising avenue for accelerated monitoring and conservation efforts [45].

Cape Santiago, located on Taiwan Island's easternmost point near Taipei, is at the intersection of the Kuroshio and longshore currents. Named by Spanish explorers 400 years ago, its 4.86 km coastline features wave-cut benches and rocky shores and is home to the small Magang fishery harbor community. With declining fishery resources driving youth to the cities, the local government, aiming to boost tourism, built a bicycle route to the coast in 2011. However, the influx of tourists engaging in harmful activities like capturing marine specimens has raised concerns about the impact on biodiversity and the coastal environment. The Cape Santiago Culture Development Association (SDCDA) was formed to protect the fishery village culture and marine ecosystem. Legally, Cape Santiago's coast is an "Ocean Resource Protected Area" under the Urban Planning Law [46], restricting construction but not specifically addressing environmental harm.

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Acknowledging the existing shortcomings in marine ecological conservation, the Ocean Affairs Council introduced the Marine Conservation Act proposal in 2019 [47]. Draft article 7 of this act empowers management authorities to designate coastal regions with significant biodiversity that require special protection as marine sanctuaries. They are also mandated to implement management measures such as ecological monitoring, as detailed in draft article 6. Thus, the SDCDA is advocating for the wave-cut bench on the western side of the fishery harbor to be recognized as a strictly regulated marine protected area. This designation would facilitate the management of environmentally detrimental actions under the Marine Conservation Act. The scientific assessment of biodiversity along this coast will be a crucial factor in determining if the area qualifies as a marine protected zone. The community members are unified in their stance and are mobilizing volunteers for coastal biodiversity CS surveys. Before furnishing the necessary scientific data to legislative bodies for the inclusion of this area as a marine protected zone, it is imperative to proactively educate tourists on the coastal ecosystem. This initiative aims to teach visitors the importance of marine conservation, discouraging activities that can harm marine life and the environment.

This study aims to assist the SDCDA in employing a CS project and AI for the conservation of Cape Santiago's intertidal biodiversity. This study has set the following objectives:

1. Create a spatiotemporal biodiversity database for the benches of Cape Santiago;
2. Assess the performance of the AI model, the data contributions from CS, and the overall impact of the collaboration;
3. Formulate an HI framework that merges CS and AI, targeting continuous monitoring and environmental education.

2. Methods

2.1. Study Area and the Citizen Scientist Project

The study area of this paper is located on the northwest side of the Cape Santiago coastline, specifically focusing on a wave-cut bench, termed the Santiago bench. This bench spans approximately 160 m in length and 70 m in width (Figure 1). The primary aim of the survey is to identify and document target marine organisms within this predefined area.

To evaluate the potential marine protected areas (MPAs), the Ocean Consecration Administration (OCA) conducted biodiversity assessments at 67 rocky shores spanning Taiwan's main island and its surrounding islands [48]. They utilized transect line and quadrat methodologies to assess marine species richness, biomass, and a range of environmental factors, including the impacts of sewage outfalls, man-made facilities, tourist activity, siltation levels, and the abundance of rock pools. By integrating both biodiversity and environmental indicators, the OCA determined the conservation priorities of these 67 rocky shores. Among the surveyed locations were four sites at Cape Santiago, including Santiago bench, Lai-Lai-1, Lai-Lai-2, and Lai-Lai-3. Notably, the Lai-Lai-2 site, located at the southeastern edge of Cape Santiago, showcased the greatest marine species diversity. Along with the neighboring Lai-Lai-3 site, both were identified as having the highest conservation value, as reported in the OCA's pilot survey [48].

The participants in the CS project were recruited by the SDCDA and underwent a comprehensive 16 h training session. This training workshop, conducted by the authors in collaboration with marine experts, encompassed topics such as rocky shore ecology, macrobenthos species identification (Table 1), AI training procedures, survey assistance methods, and environmental education. To enhance their training, materials from a prior survey compiled from the author's dataset [49] that identified 13 phyla and cataloged 234 marine species, including a new marine flatworm species [50], were provided, complemented by images of each species previously documented in the region. The main responsibilities assigned to the CS participants were twofold: data collection through field surveys and public education regarding the intertidal environment.

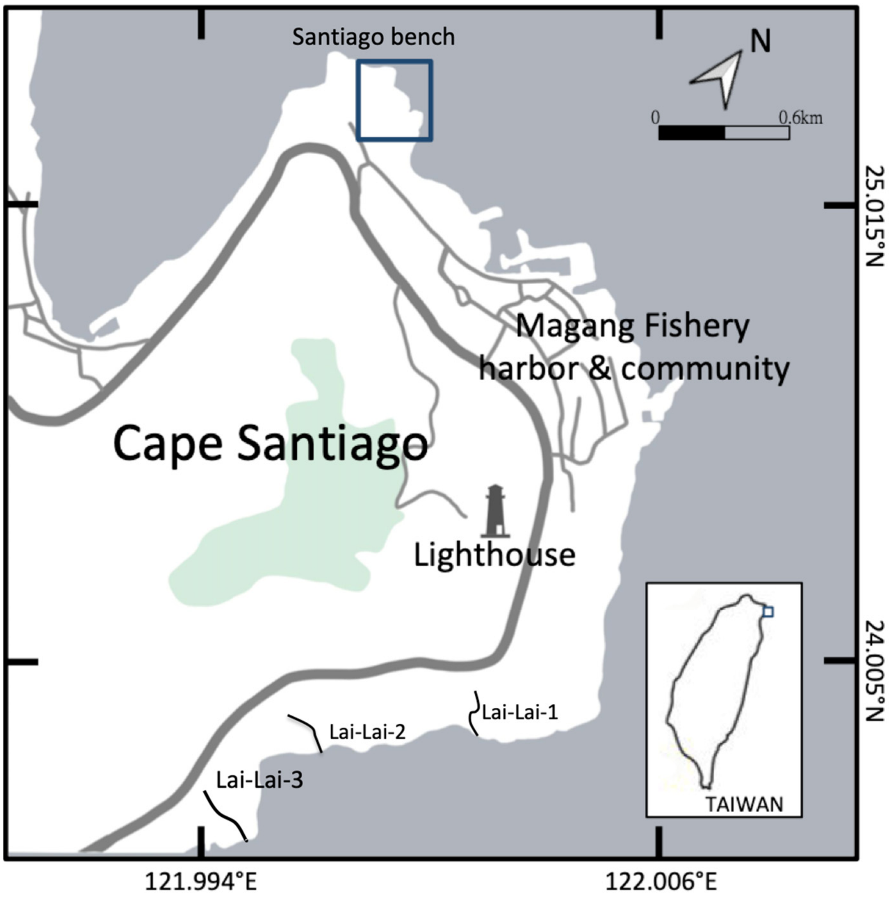

Figure 1. Location of the study site at Cape Santiago with its position within Taiwan highlighted (inset) and the three survey lines conducted by the OCA.

Table 1. The structure of the macrobenthos in the study area of marine species of Santiago bench.

Kingdom	Phylum	Common Names	Species Numbers
Animalia	Porifera	Sponges	8
	Bryozoa	Bryozoans, Moss Animals	4
	Mollusca	Cowries, Chitons, Sea Slugs, Octopuses, Oysters	72
	Arthropoda	Crabs, Shrimps, Barnacles	22
	Annelida	Segmented Worms	8
	Coelenterate	Corals, Sea Anemones, Jellyfishes	10
	Echinoderms	Sea Stars, Sea Urchins, Sea Cucumbers	27
	Nemertina	Ribbon Worms	2
	Platyhelminthes	Flatworms	8
	Chordata	Tunicates, Vertebrates, Fishes, Sea Snakes	39
Plantae	Chlorophyta	Green Algae	9
	Rhodophyta	Red Algae	19
	Chromophyta	Brown Algae	6

The survey protocol, derived from the Ocean Consecration Administration's (OCA) transect line method, required two individuals to methodically search and document marine species along a designated transect line, spanning from the high tide zone to the low tide area of the shore. The survey procedure was conducted by volunteers who had previously received a CS training workshop. During the survey, the participants followed a pre-set route marked by the transect line, photographing all marine specimens encountered and recording the quantities of specific target species on survey forms. Following the survey, the collected data and images were systematically compiled and uploaded to create a comprehensive training dataset for future artificial intelligence (AI) training sessions.

2.2. Training AI Model and AI Performance Evaluations

The convolution neural network (CNN) is a cornerstone in AI models for image pattern extraction and recognition [51]. R-CNN and YOLO, both built on the CNN framework, can distinguish various objects within an image [52,53]. The YOLOv5s [54] model was chosen for this study because of its high calculating speed and accuracy in detecting marine life in natural settings. YOLOv5s, being a deep-learning approach in machine vision, requires comprehensive training on an extensive image dataset to perform optimally [55,56]. The images of organisms from the participants' field survey dataset were meticulously identified and annotated as 'instances' using the open-source Python program labelImage (https://github.com/HumanSignal/labelImg, accessed on 10 July 2022). Each instance was marked as a bounding box with its location, size, and common name within the image. Effective AI recognition of a particular specimen necessitates a substantial image database for that specimen, typically comprising 200 or more instances, as per our experience. Consequently, species that are commonly observed at the research site are usually selected for AI training. To keep participants engaged, we also include a selection of rare target species, like sea hares and blue-ringed octopuses, encouraging participants to search for and document these less frequently encountered organisms. These annotated images were then compiled into a training dataset for YOLOv5s. All datasets were randomly split with 80% allocated for training and 20% for validation. Training was conducted on Linux desktop computers equipped with an RTX3090-24G GPU, using hyperparameters that encompassed a pre-trained weight, a training batch size of 32, an image resolution of 800 × 800, and a learning epoch of 200.

Two primary tasks need to be executed by a trained AI model. The first involves identifying target species instances from an image, while the second requires the accurate prediction of the specific species' common name, distinguishing it from other species. The AI model's predictions for any given specimen can be categorized into four possible outcomes:

4. Correctly identifying the actual species—true positive (TP).
5. Accurately recognizing a species other than the target—true negative (TN).
6. Missing the identification of the actual species—false negative (FN).
7. Incorrectly labeling a different species as the target species—false positive (FP).

The outcomes of distinguishing between various species can be depicted in a two-dimensional table, commonly referred to as a confusion matrix. In this matrix, the actual species are represented on the x-axis, while the predicted species appear on the y-axis (refer to Figure 2). The overall model's performance was assessed using Equations (1), (2), and (4):

$$precision = \frac{TP}{TP + FP} \tag{1}$$

$$recall = \frac{TP}{TP + FN} \tag{2}$$

To calculate the ratio of the area in the predicted instance bounding box B_p overlapping the area of the actual ground truth box B_g, the intersection of union, IoU, formula is used as follows:

$$IOU = \frac{aera\ |Bp \cap Bgt|}{aera\ |Bp \cup Bgt|} \tag{3}$$

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The $mAP_{0.5}$ Equation (3) measures the averaged precision value of all the cases when the *IOU* is 50% threshold area overlap.

$$mAP_{0.5} = \frac{1}{n}\sum\nolimits_{i=1}^{n} AP_{category\ i} \quad when\ IoU\_threshold = 0.5 \tag{4}$$

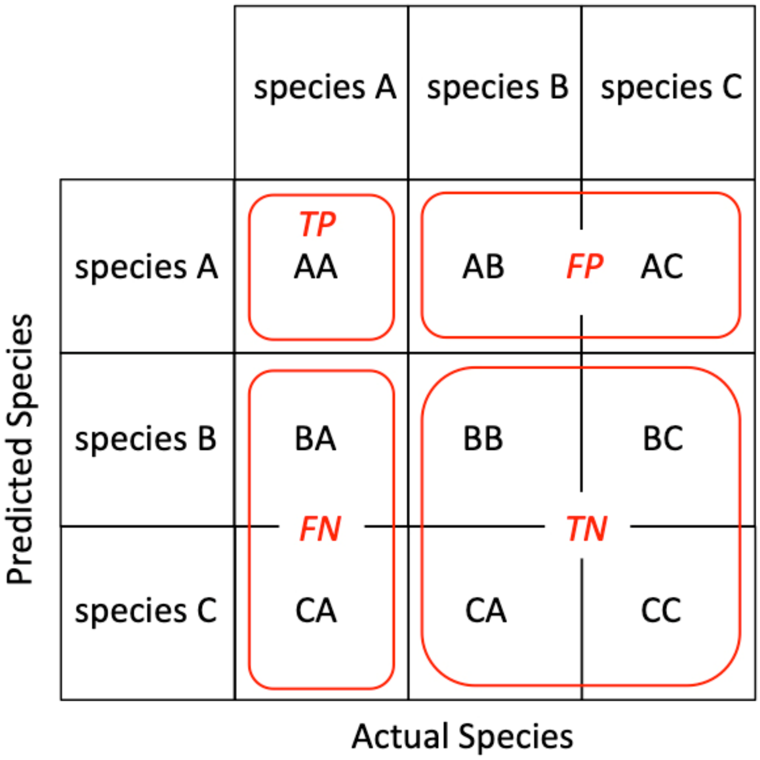


Figure 2. An example of a 3 × 3 multi-class confusion matrix with actual species as x-axis/row grids and predicted species as y-axis/column grids. While focusing on class A, the AA grid is true positive, TP, the rest of the row grids are false positive, FP, the rest of the column grids are false negative, FN, and the rest of the grids except all above grids are all true negative, TN.

2.3. Hybrid Intelligence Criteria for CS and AI Synergy

To investigate the potential synergy between CS and AI in forming HI, we adopted the operational definition of hybrid intelligence (HI) from [57], which is based on three criteria:

8. **Collectiveness:** This emphasizes the collaboration between humans and AI with the aim of collectively addressing a task to achieve a system-level goal. It is acknowledged that individual agents might have sub-goals that deviate from the overarching system objective.
9. **Solution Superiority:** This asserts that the combined sociotechnical system, which includes both humans and AI, produces results surpassing what individual agents, whether human or AI, could achieve independently.
10. **Mutual and Continuous Learning:** The system shows consistent improvement, both collectively and at the individual component level (human and AI). This continuous enhancement signifies persistent learning and development from both parties.

3. Results

3.1. Survey Protocols

Initially, the survey protocol was adapted from the OCA's methodology [48]. This approach involved setting up 10 transect lines on the Santiago bench within the determined survey zone. The survey groups, each comprising two members, aligned with these lines. Therefore, a total of 10 groups worked in tandem, collecting data and photographs for AI training. The primary objective was to document the time and spatial occurrence of marine species. Upon implementation, some challenges with the original proposal survey protocol (PSP) (Figure 3a) became apparent. Some species, like the sea hare, were absent during the summer surveys. Considering the route's dual function as a prospective educational pathway, a looped configuration was determined to be more suitable than a linear design. This feedback led to the development of an adaptive survey protocol (ASP). The pivotal change in the adaptive survey protocol involved the survey route. Instead of traversing directly from the shore to the sea, the route now followed grooves (GRV) parallel to the coastline. These grooves acted as paths that led to four tidal pools (TP) and four grooves (GRV). This revised protocol offered flexibility in group sizes, and the teams could now conduct their surveys asynchronously, adhering to the predetermined route (Figure 3b).

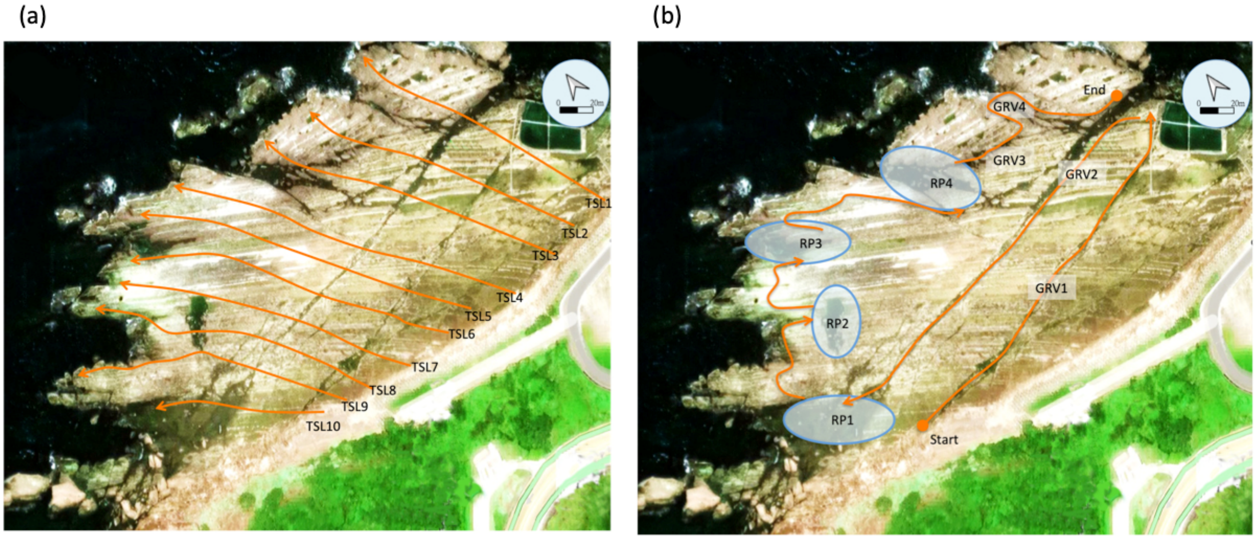
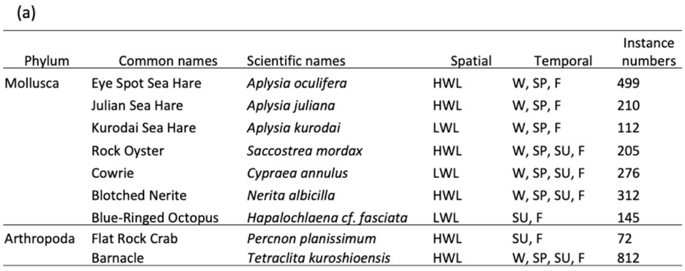


Figure 3. The survey transect routes of different survey protocols. (**a**) The routes of ten transect lines (TSL) of the proposed survey protocol (PSP), and (**b**) a loop comprised of 4 grooves (GRV) and 4 rock pools (RP) of the adaptive survey protocol (ASP).

The survey data are categorized based on both temporal and spatial factors. Temporal data capture the season during which the survey was conducted, categorized into spring (SP), summer (SU), autumn (F), and winter (W). The surveys were uniquely timed to coincide with low tide moments, allowing for the CS participants to access the exposed bench. Spatial data are differentiated based on tide levels: high tide level (HTL) and low tide level (LTL). As the tide recedes and the Santiago bench is unveiled, areas retaining water in depressions are labeled as LTL, while areas showcasing organisms above the water surface are designated as high water level (HWL). These designations aid in recording the spatial distribution of marine organisms (Figures 4a and 5a).

3.2. *Proposal Survey Protocol and AI Training*

From the proposed survey protocol, we garnered a collection of 1301 photographs that showcased nine distinct marine species, complete with their spatial and temporal distribution. The total annotated instances across all specimens amounted to 2643 (Figure 4a). Utilizing this dataset, we trained the PSP YOLOv5s neural network, achieving a performance marked by a precision of 0.96175, recall of 0.93533, and mAP_0.5 of 0.95485. An examination of the confusion matrix indicated high true positive (TP) values for almost all species. Notably, barnacles and oysters registered TP values of 0.83 and 0.87, respectively. All other species achieved impressive TP values exceeding 0.97 with some even reaching a perfect score of 1.0 (100%) (Figure 4b).



(a)

Phylum	Common names	Scientific names	Spatial	Temporal	Instance numbers
Mollusca	Eye Spot Sea Hare	*Aplysia oculifera*	HWL	W, SP, F	499
	Julian Sea Hare	*Aplysia juliana*	HWL	W, SP, F	210
	Kurodai Sea Hare	*Aplysia kurodai*	LWL	W, SP, F	112
	Rock Oyster	*Saccostrea mordax*	HWL	W, SP, SU, F	205
	Cowrie	*Cypraea annulus*	LWL	W, SP, SU, F	276
	Blotched Nerite	*Nerita albicilla*	HWL	W, SP, SU, F	312
	Blue-Ringed Octopus	*Hapalochlaena cf. fasciata*	LWL	SU, F	145
Arthropoda	Flat Rock Crab	*Percnon planissimum*	HWL	SU, F	72
	Barnacle	*Tetraclita kuroshioensis*	HWL	W, SP, SU, F	812

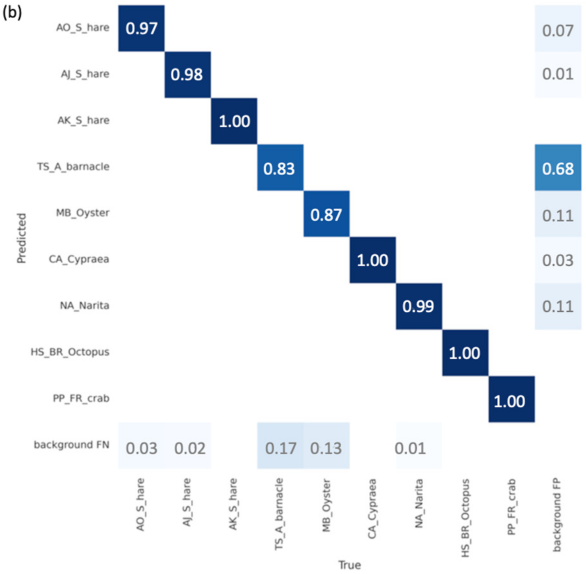
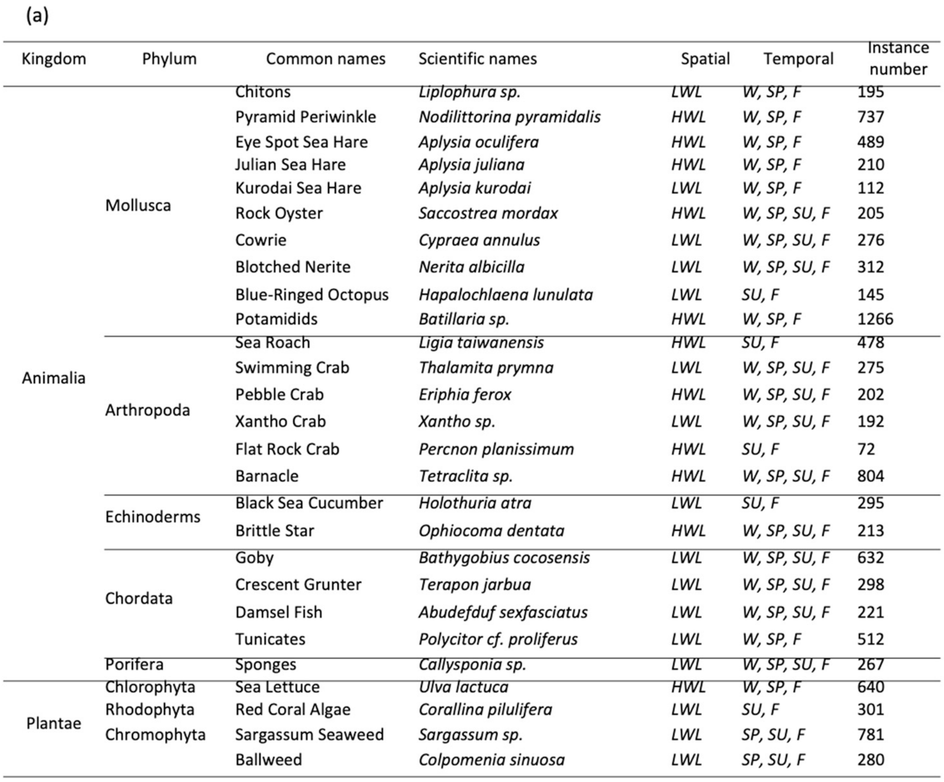


Figure 4. (**a**) Displays the species common name, scientific name, spatial distribution (high water level (HWL) or low water level (LWL)), temporal distribution (spring (SP), summer (SU), autumn (F), winter (W)), and instance number of 9 species collected and used for training YOLOv3 following adaptive protocol surveys conducted by CS participants. (**b**) Shows the confusion matrix true positive (TP) results for different species classes.



(a)

Kingdom	Phylum	Common names	Scientific names	Spatial	Temporal	Instance number
Animalia	Mollusca	Chitons	*Liplophura sp.*	*LWL*	*W, SP, F*	195
		Pyramid Periwinkle	*Nodilittorina pyramidalis*	*HWL*	*W, SP, F*	737
		Eye Spot Sea Hare	*Aplysia oculifera*	*HWL*	*W, SP, F*	489
		Julian Sea Hare	*Aplysia juliana*	*HWL*	*W, SP, F*	210
		Kurodai Sea Hare	*Aplysia kurodai*	*LWL*	*W, SP, F*	112
		Rock Oyster	*Saccostrea mordax*	*HWL*	*W, SP, SU, F*	205
		Cowrie	*Cypraea annulus*	*LWL*	*W, SP, SU, F*	276
		Blotched Nerite	*Nerita albicilla*	*LWL*	*W, SP, SU, F*	312
		Blue-Ringed Octopus	*Hapalochlaena lunulata*	*LWL*	*SU, F*	145
		Potamidids	*Batillaria sp.*	*HWL*	*W, SP, F*	1266
	Arthropoda	Sea Roach	*Ligia taiwanensis*	*HWL*	*SU, F*	478
		Swimming Crab	*Thalamita prymna*	*LWL*	*W, SP, SU, F*	275
		Pebble Crab	*Eriphia ferox*	*HWL*	*W, SP, SU, F*	202
		Xantho Crab	*Xantho sp.*	*LWL*	*W, SP, SU, F*	192
		Flat Rock Crab	*Percnon planissimum*	*HWL*	*SU, F*	72
		Barnacle	*Tetraclita sp.*	*HWL*	*W, SP, SU, F*	804
	Echinoderms	Black Sea Cucumber	*Holothuria atra*	*LWL*	*SU, F*	295
		Brittle Star	*Ophiocoma dentata*	*HWL*	*W, SP, SU, F*	213
	Chordata	Goby	*Bathygobius cocosensis*	*LWL*	*W, SP, SU, F*	632
		Crescent Grunter	*Terapon jarbua*	*LWL*	*W, SP, SU, F*	298
		Damsel Fish	*Abudefduf sexfasciatus*	*LWL*	*W, SP, SU, F*	221
		Tunicates	*Polycitor cf. proliferus*	*LWL*	*W, SP, F*	512
	Porifera	Sponges	*Callysponia sp.*	*LWL*	*W, SP, SU, F*	267
Plantae	Chlorophyta	Sea Lettuce	*Ulva lactuca*	*HWL*	*W, SP, F*	640
	Rhodophyta	Red Coral Algae	*Corallina pilulifera*	*LWL*	*SU, F*	301
	Chromophyta	Sargassum Seaweed	*Sargassum sp.*	*LWL*	*SP, SU, F*	781
		Ballweed	*Colpomenia sinuosa*	*LWL*	*SP, SU, F*	280

Figure 5. *Cont.*

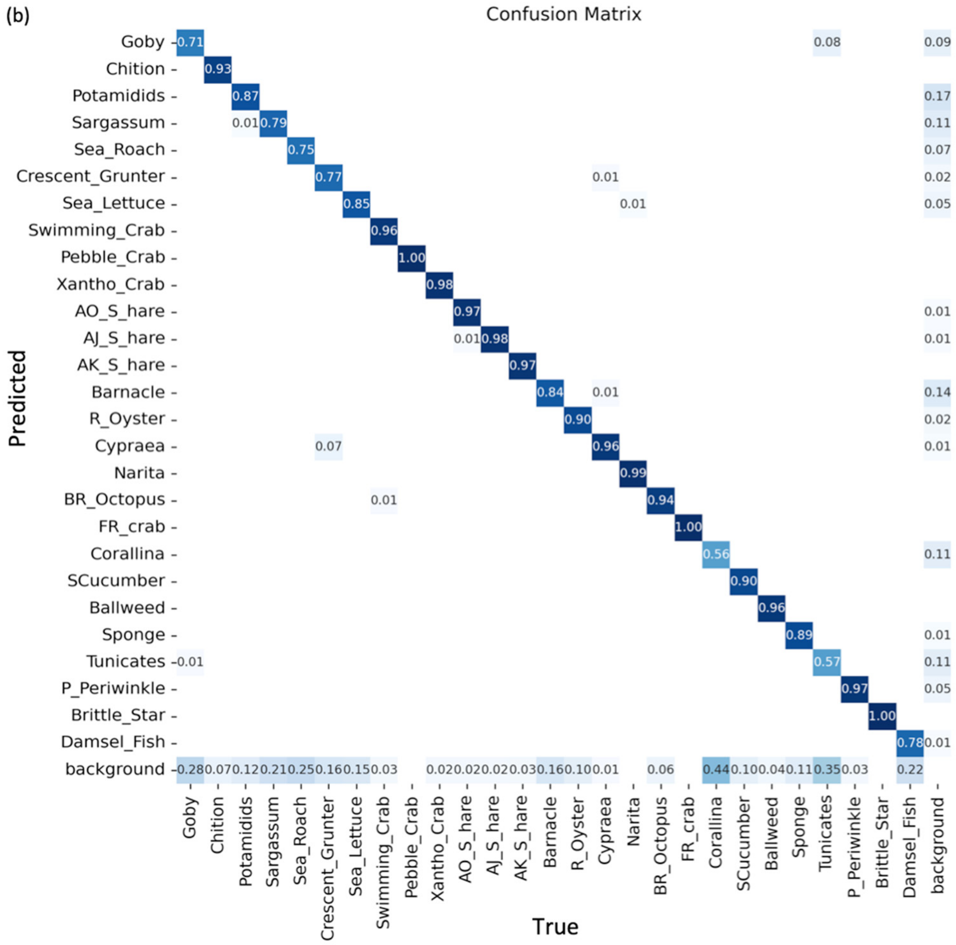


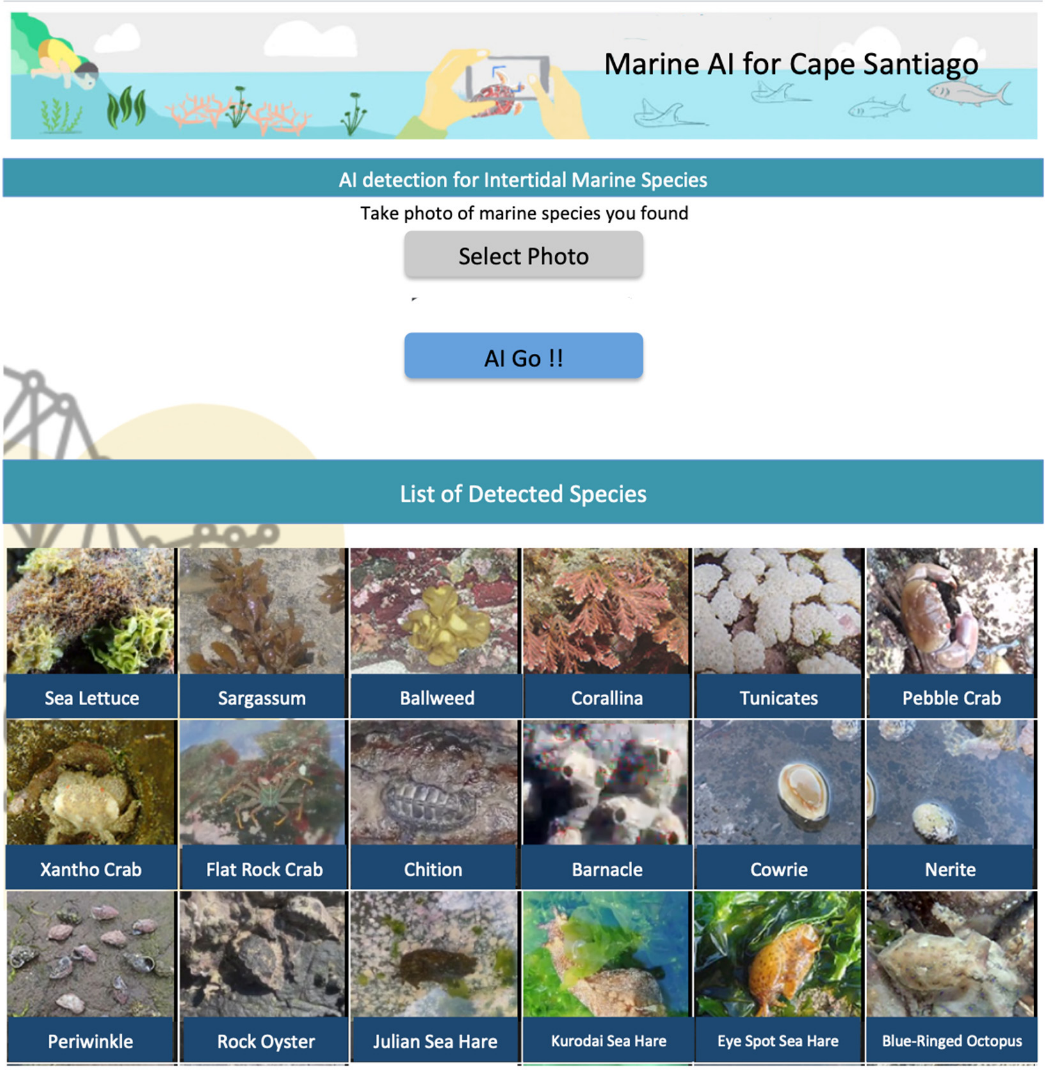
Figure 5. (**a**) Displays the species common name, scientific name, spatial distribution (high water level (HWL) or low water level (LWL)), temporal distribution (spring (SP), summer (SU), autumn (F), winter (W)), and instance number of 27 species collected and used for training YOLOv3 following adaptive protocol surveys conducted by CS participants. (**b**) Shows the confusion matrix true positive (TP) results for different species classes. The darker color shows the higher TP accuracy.

3.3. Adaptive Survey Protocol and AI Training

Based on the integration of the ASP and the earlier PSP, we obtained a comprehensive collection of 5461 photographs that depict 27 distinct marine species. This dataset not only showcases the spatial and temporal distribution of these species but also includes a total of 7729 annotated instances (Figure 5a). Leveraging this enriched dataset, we trained the ASP YOLOv5s model, which yielded a performance evaluation with a precision of 0.87412, recall of 0.85843, and mAP_0.5: of 0.8707. A deeper dive into the confusion matrix, post enhancement of instance and species counts, revealed that the true positive (TP) values for species like red coral algae (*Corallina* sp.) and tunicates were the lowest, registering at 0.56 and 0.57, respectively. Notably, most of the species TP values from the PSP remained unchanged. The earlier low TP values observed in the PSP dataset for barnacles and oysters showed slight improvements, rising from 0.83 to 0.84 and 0.87 to 0.90, respectively (Figure 5b).

3.4. Deployment of AI for In Situ Identification

An application program interface (API) was developed using the Python programming language to facilitate a web-based interface (Figure 6). This interface hosts the trained AI model dedicated to marine specimen recognition and is stationed on a cloud server for efficient specimen identification tasks. Crafted with the intent to aid the CS participants during surveys or environmental educational endeavors, this tool proves invaluable in real-time specimen identification. On encountering marine organisms in their natural habitat, users can snap photos using their mobile devices and promptly upload them for instant AI-based identification. Upon receiving the image, the API communicates with the AI model to carry out the recognition process, subsequently relaying the results back to the user (Figure 7). This streamlined process greatly enhances the efficiency and accuracy of specimen surveys and educational activities.



Marine AI for Cape Santiago

AI detection for Intertidal Marine Species

Take photo of marine species you found

List of Detected Species

Figure 6. The program interface API incorporates an AI recognition service. Users can utilize the provided AI recognition capabilities to search for organism in the field. When they encounter a suspected specimen (pictures listed below as a guide), they can capture a photo and upload it from their mobile phones to the server to request AI identification.

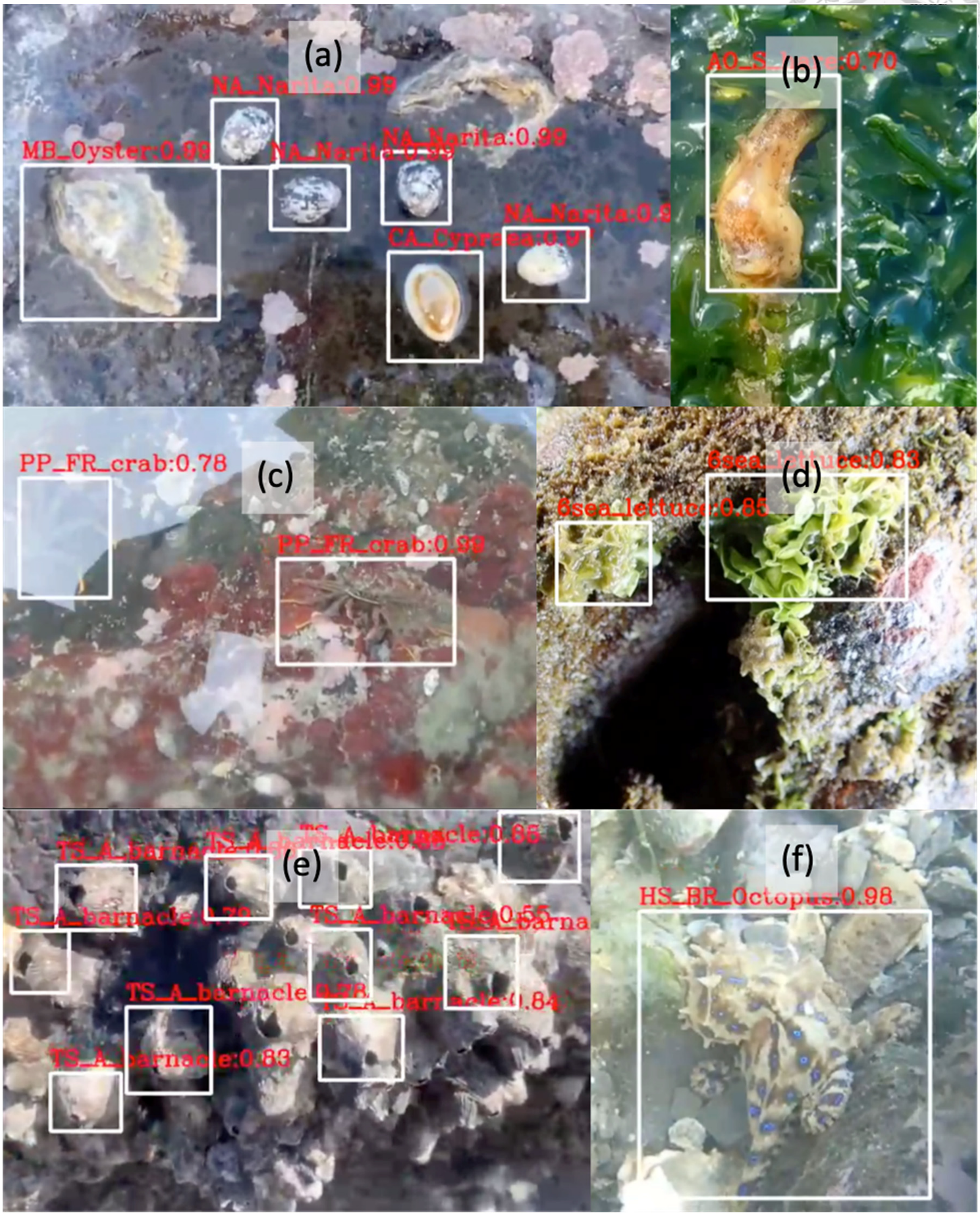


Figure 7. Examples of AI-identified specimen instances: (**a**) 4 blotched-nrites, 1 cowrie, and 1 rocky oyster, (**b**) 1 eye spot sea hare, (**c**) 2 flat rock crabs, (**d**) 2 sea lettuce, (**e**) 10 barnacle shells, (**f**) 1 blue-ringed octopus.

4. Discussions

4.1. Adaptive Survey Protocol for Rocky Intertidal Biodiversity

The Ocean Conservation Administration's proactive survey [48] initiative aligns with the prescriptive Marine Conservation Act draft, aiming to foster a deeper understanding of Taiwan's extensive coastline, spanning approximately 1600 km, including the rocky intertidal ecosystems. Among the 67 identified survey sites, each was meticulously assessed for environmental and biological diversity. This assessment entailed a 60 m transect-line study from the high tide to the low tide mark, where researchers diligently documented observable marine species within a 60 min timeframe. Complementary to this, quadrat photographs were used to further analyze species presence and abundance.

However, the photographic method within the quadrat has its limitations, primarily disturbing mobile species, which may lead to an underrepresentation of non-sessile organisms. This method also struggles with capturing seasonal biodiversity variations, as demonstrated with the surveys conducted in early July at Cape Santiago. Seasonal dynamics, such as the absence of green algae due to summer conditions, could significantly skew the diversity index, omitting critical faunal dependencies.

The geological complexity of Cape Santiago's intertidal zones with its pits, grooves, crevices, and rock pools inherently impacts marine biodiversity. The intricate structures provide a multitude of microhabitats that support a rich array of life [58]. Davidson et al. [59] found that the diversity in mobile taxa can be twice as high as that in sessile taxa with sessile organisms presenting far greater abundance. This indicates that Cape Santiago's biodiversity is likely to exhibit considerable spatial and temporal variations that are influenced by monsoons, tides, water temperature, and sunlight exposure.

Addressing the spatial–temporal complexities and survey feedback from the CS participants, the adaptive survey protocol (ASP) was designed to overcome the limitations of the OCA transect-line method. It aims to prevent trampling damage to microhabitats by modifying survey routes to a single track along bench crevices (Figure 3), allowing for the CS participants to survey at their convenience, including nighttime. This flexible approach expands the spatial–temporal scope of data collection, which is essential for monitoring biodiversity changes.

4.2. Synergic Learning between CS and AI

In this study, a collaborative learning system that integrates CS and AI has been established. This system enables a symbiotic learning relationship where AI benefits from human-generated data and humans refine their knowledge through AI feedback, promoting mutual learning over extended periods. The flow of information and learning is illustrated in Figure 8. The CS participants, through workshops focusing on specimen identification and AI training, improve their skills and are, thus, able to contribute more effectively. They collectively gather extensive image datasets, 1301 images from PSP and 5461 images from ASP (shown in Figure 8c), which are crucial for effective PSP and ASP YOLOv5s model training. The outcomes of the training then provide insights, 0.96175 precision for PSP and 0.87412 precision for ASP, into the collective data quality of different survey protocols (Figure 8d).

Utilizing an online AI tool, the CS participants enhance the AI's identification capabilities through real-time data provision. This iterative process may refine the YOLOv5s model, which is our offline solution algorithm (offSA) that, after rigorous training using images from CS activities, is now operational on a server (Figure 8e). A user-friendly interface (Figure 6) has been established to streamline access to the online solution algorithm (onSA), serving both the CS participants (CSPs) and tourists engaged in educational programs (Figure 8a). The interface offers instant identification results (Figure 8b) and is integral to data collection for continuous AI training. This strategic implementation forms a dynamic feedback loop with data from queries contributing to successive training cycles, progressively enhancing the AI model's accuracy (Figure 8a,f).

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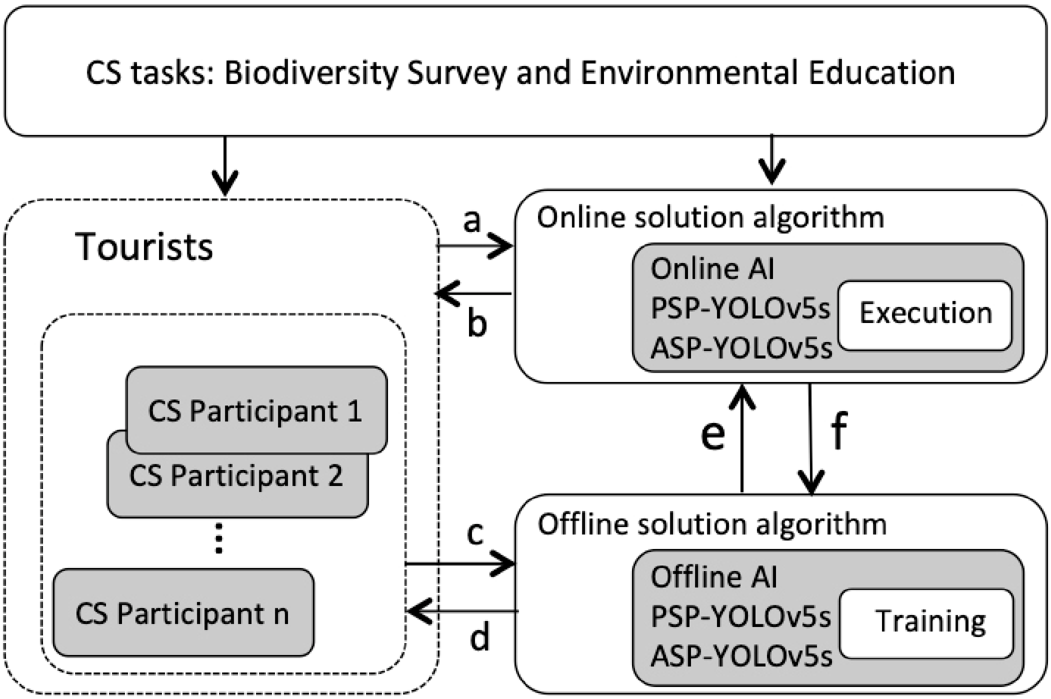

Figure 8. The information flow diagram (IFD) illustrating "Tier 3: hybrid intelligence (HI) at the collective level" adapted from Ref. [43]. Please refer to the accompanying text for details.

A crucial aspect of citizen science (CS) projects is maintaining data quality, a task complicated by the varied experience levels of the contributors [60–62]. This study shifts from individual to collective intelligence evaluations using AI model performance as a proxy for data quality assessment. Participants engaged in PSP may question whether their dataset of 1301 images with 2643 annotations sufficiently trains the PSP YOLOv5s model. The AI's performance, precision of 0.96175, recall of 0.93533, and mean average precision (mAP_0.5) of 0.95485, suggests robust training efficacy. Similarly, those conducting ASP with 5461 images and 7729 annotations must consider if their dataset is adequate. The ASP model's results, precision of 0.87412, recall of 0.85843, and mAP_0.5 of 0.8707, pose questions about disparities in performance. An inquiry arises: What factors contribute to these differences, and can the ASP model achieve the PSP model's level of accuracy?

Through confusion matrix analysis, the research evaluates the dataset quality for different models. Table 2, derived from the confusion matrices (Figures 4 and 5), details instances and their corresponding true positives (TP) recognized by the models. Certain species, such as the red coral algae (*Corallina* sp.) and tunicates, exhibit TP values that do not meet the desired standard. Despite their substantial representation in the training dataset with 301 and 512 instances, respectively, they achieved TP values of only 0.56 and 0.57. This stands in stark contrast to the Kurodai Sea Hare that, with merely 112 instances in the ASP dataset, secured a TP value of 0.98 (as shown in Table 2.). This discrepancy signals a challenge for the AI model in recognizing these specimens accurately, highlighting a need for improved data quality in both collection and annotation by the CS participants. Thus, the CS participants learn that data collection and annotation processes require further enhancement for better AI training outcomes.

Table 2. The instance amount and true positive (TP) values of different species data collected with the proposal survey protocol (PSP) and adaptive survey protocol (ASP).

Common Name	**PSP**		**ASP**	
	Instance	**Species TP**	**Instance**	**Species TP**
Eye Spot Sea Hare	499	0.97	489	0.97
Julian Sea Hare	210	0.98	210	0.98
Kurodai Sea Hare	112	1.00	112	0.98
Barnacle	812	0.83	804	0.84
Rock Oyster	205	0.87	205	0.90
Cowrie	276	1.00	276	0.96
Blotched Nerite	312	0.99	312	0.99
Blue-Ringed Octopus	145	1.00	145	0.94
Flat Rock Crab	72	1.00	72	1.00
Goby	NA		632	0.71
Chition	NA		195	0.93
Potamidids	NA		1266	0.87
Sargassum	NA		781	0.79
Sea Roach	NA		478	0.75
Crescent Grunter	NA		298	0.77
Sea Lettuce	NA		640	0.85
Swimming Crab	NA		275	0.96
Pebble Crab	NA		202	1.00
Xantho Crab	NA		192	0.98
Red Coral Algae (Corallina)	NA		301	0.56
Ballweed	NA		280	0.96
Sponge	NA		267	0.89
Tunicates	NA		512	0.57
Pyramid Periwinkle	NA		737	0.97
Brittle Star	NA		213	1.00
Damsel Fish	NA		221	0.78

4.3. The Criteria for Developing Hybrid Intelligence

Ref. [57] suggests three criteria for the development of a hybrid intelligence system. The first criterion, "collectiveness" within the context of HI pertains to the concerted effort of CS and AI to fulfill a system-level objective. In this study, the YOLO object-detection model necessitates an extensive array of specimen photographs with annotated instances for effective model training, a process reliant on the gradual and cumulative data collection by various CS participants over multiple surveys. Since individual contributions may be limited due to time constraints and unpredictable specimen appearances, aggregating data across different times is crucial for capturing species diversity. AI, thus, emerges as a catalyst, unifying the efforts of the CS participants toward a common goal, the comprehensive documentation of rocky intertidal ecosystem biodiversity.

The second criterion for effective HI is the achievement of "superior outcomes" compared to those possible with CS or AI in isolation. Repetitive surveys and environmental education tasks are often taxing, potentially diminishing volunteer enthusiasm. However, the assurance that their diligent survey efforts contribute to AI databases for educational purposes coupled with the positive feedback received from leveraging AI's novel technology sustain participant motivation and ensure ongoing involvement, a testament to the project's operational success.

Lastly, the establishment of "perpetual learning" constitutes the third criterion of HI. The AI's confusion matrix serves as a tool for assessing the quality of data for specific species, encouraging CS participants to persist in their data collection efforts. This ongoing collection process is not just during formal surveys but also through interactive specimen identification using AI during educational activities. As data accumulate, they refine the training dataset, enhancing AI's recognition capabilities. Moreover, AI becomes an

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invaluable aid for newcomers in CS, facilitating rapid species identification skill acquisition and perpetuating the educational growth of the entire CS community.

4.4. AI and Citizen Science: A Socio-Technological Synthesis

Our study underscores the importance of not only building an AI model but also managing the socio-technological integration between AI and CS to ensure the effective functioning of HI. Inspired by McClure et al. [45], who delineated eight key attributes critical to CS and AI integration, we delved into these attributes, as they provide a comprehensive framework for managing HI systems within our research domain. These attributes and their complex interrelationships with AI and CS, alongside their associated tasks, are depicted in a mind map (Figure 9) and are further dissected in the subsequent sections.

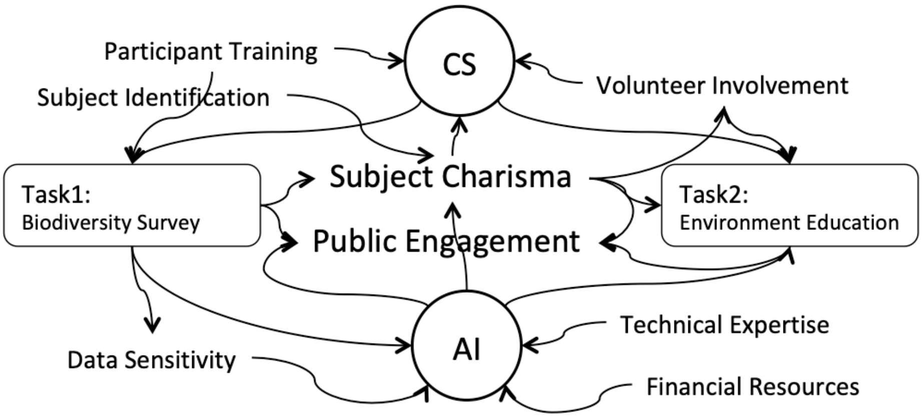

Figure 9. The illustration depicts the integrative mind map of the hybrid intelligence system, encompassing components of CS and AI, along with two distinct tasks. The map is further characterized by eight attributes crucial for effective system management. The directional arrows within the diagram indicate the influences between components and attributes. Detailed explanations can be found in the accompanying text.

11. Subject Charisma:

The intertidal zone of reef rocks teems with diverse marine life and is subject to dynamic ecological changes, presenting urbanites from terrestrial settings with a vivid and elusive tableau of the sea's inhabitants. These marine creatures, often sporting distinctive and vibrant appearances, make the zone an accessible, enigmatic, and captivating new realm that beckons for repeated exploration. Notably, charismatic species like the Eye Spot Sea Hare (*Aplysia oculifera*), which bears a resemblance to the popular cartoon character Pikachu, play a crucial role in heightening the involvement of CS participants and visitors. The combination of such appealing creatures and the deployment of smartphone-based AI tools for specimen identification enhances the marine biodiversity exploration into an engaging and educational ecological quest. This synergy significantly boosts environmental education initiatives and fosters public engagement.

12. Subject Identification:

Specimen recognition represents a considerable challenge, particularly for tourists with limited knowledge of marine biodiversity. Our study's protocol addresses this by providing a list of species that accounts for their varied appearances throughout the seasons. Such measures ensure that tourists can identify marine life during their visit, enriching their encounter with marine biodiversity and making the identification process an educational experience in its own right.

13. Public Engagement:

The hybrid intelligence-driven online AI service introduced in this study is a testament to the power of engaging the public in environmental stewardship. By enabling visitors to

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identify organisms within the intertidal zone through an engaging process, we not only educate but also discourage detrimental behaviors, such as the capture of marine life. This strategy is key to garnering support for the conservation efforts outlined in 8. financial considerations.

14. Volunteer Involvement:

The success of CS initiatives is heavily reliant on the dedication of volunteers. Despite the logistical challenges posed by the remote location of our study site, the dynamic nature of marine biodiversity here continually inspires local volunteers. The incorporation of AI technology into their routine surveys has been instrumental in sustaining their enthusiasm, as they often discover previously unrecorded species, underscoring the value of their involvement and the importance of their continued participation.

15. Participant Training:

Training for CS participants is designed to be both accessible and practical, utilizing localized survey protocols and tailored species lists to navigate the complexities of marine biodiversity. Ongoing training workshops are scheduled to mitigate emerging challenges and ensure participants are well-equipped to conduct AI-assisted field surveys, which are vital for the AI's continuous learning, as highlighted in 6. technical expertise.

16. Technical Expertise:

The gradual elevation of expertise among participants through hands-on surveys and engagement with online resources or marine experts highlights the mutual learning process central to HI. By contributing to image annotation, participants provide valuable data that enhance the AI training process and the model's subsequent performance.

17. Data Sensitivity:

Sensitive handling of the images uploaded by participants for AI identification is paramount. Our protocol ensures that users are aware their contributions are confidential and used solely for the purpose of enhancing the AI model. Such transparency is essential in maintaining trust and encouraging the responsible sharing of data.

18. Financial Considerations:

The choice between establishing a dedicated AI computing infrastructure versus using cloud AI services involves significant financial deliberations. Our decision to develop our own system reflects our commitment to research flexibility. Yet, the financial sustainability of both the AI infrastructure and the CS project remains a key concern, one that is necessary for the unbroken operation of HI and the achievement of our conservation goals.

By dissecting and addressing these attributes, our research not only provides a technical blueprint for AI–CS integration but also offers insights into the socio-technological considerations that underpin the successful deployment of HI systems for environmental conservation.

4.5. The Role of Hybrid Intelligence in MPA Designation

Designing a marine protected area (MPA) is a complex task. As per the recent updates to the US National Marine Sanctuaries Act, effective management and a comprehensive understanding of the area over a decade are prerequisites [63]. Addressing these challenges, particularly those related to personnel resources, the OCA report has indicated the valuable role citizen scientists could play [48].

By collating specimen survey data to create training materials, CS participants can perform year-round, consistent monitoring within specified areas. This method paves the way for a deeper understanding of the seasonal patterns within marine communities and yields more detailed data on the temporal and spatial diversity of marine ecosystems.

HI, which merges the collective efforts of citizen science and artificial intelligence (AI), establishes a progressive framework for marine species education and motivates the public to partake in regular spatiotemporal surveys. This process of collecting data at different times and locations is crucial to meeting the comprehensive training and data collection demands essential for setting up an MPA.

Beyond the ecological considerations, MPAs situated near urban areas face a wider spectrum of socio-ecological challenges. Not only must they address the transformation of the economic activities of fishing communities, but MPAs in suburban locales also present opportunities for urbanites to reconnect with nature, alleviating the stress of confined urban living conditions [64]. Through participatory design involving the community and the public, HI serves as a biophilic instrument that enhances urban livability.

5. Conclusions

Effective system management enhances the integration of CS and AI within the hybrid intelligence system, providing robust solutions for intertidal biodiversity conservation initiatives at Cape Santiago. Field surveys undertaken by trained CS participants generate image datasets crucial for AI training. The training outcomes, representing a transformation of multifaceted image data into numerical values, facilitate intertidal biodiversity analysis and reflect the overarching quality of data procured by all CS participants. Once an AI model is trained and available on the Web, it functions as a marine organism detection tool, supporting CS participants in their environmental education endeavors, especially for tourist instruction. Continuous feedback from user interactions precipitates holistic improvements in the HI system, encompassing the fine-tuning of survey methodologies, the prioritization of specific species, and the customization of AI tools to meet the demands of in situ environmental education. Strategically managing this HI not only fosters sustained engagement among CS participants but also bolsters broader public involvement, thereby strengthening advocacy for the prospective designation of the region as a marine protected area.

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