Emerging Computational Methodologies for Transparency in Fisheries

by

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Abstract

Our ocean covers over 70% of our planet. It is the world's largest food system, supporting the food security of several billion people and livelihoods for hundreds of millions of people globally. Conservation of ocean ecosystems refers to the study of marine ecosystems and their functions while the act of ocean conservation is protecting and preserving ecosystems in oceans and seas through planned management in order to prevent the exploitation of its' resources. As the human population has dramatically increased, as has the pressure of human impact on ocean ecosystems resulting in overfishing and causing increased extinction rate of marine species and destruction of marine environments. Harnessing the great leaps the world has experienced in computational processing for marine applications is not a question of when, but how. This body of research lays the foundations for a novel field - computational marine stewardship. An assemblage of technical innovations that hold the potential for integrating greater transparency in seafood supply chains, this research informs the dialogue around developing fisheries management technologies towards greater marine stewardship efforts.

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Chapter 1

Introduction

The ocean is the world's largest food system, supporting the food security of several billion people and livelihoods for hundreds of millions of people worldwide [5]. Seafood is produced via wild-capture fisheries and aquaculture farming, and is the most highly traded food commodity on the planet. The governance systems for seafood production are complex, and vary depending on jurisdiction, geography, production mode, markets, and other factors. Every year, hundreds of species are harvested or farmed and move into global seafood markets via complex, and highly fragmented supply chains that face challenges in transparency and accountability [30, 15]. Opacity in seafood supply chains has made it easy to mask harmful practices such as seafood fraud, illegal, unregulated and unreported fishing (IUU), and human rights abuses [24, 49].The lack of transparency has presented a significant challenge to the sector, driving illegal, irresponsible and harmful production practices that are compromising ocean ecosystems and the people that rely on them.

Solving these issues is critical to ensure that the ocean can continue to play an important role in global food and livelihood security. According to U.N. estimates, the world's population will increase by 33% by 2050 — meaning 2.4 billion more mouths to feed — and the world must produce 70 percent more food to meet the greater demand. If sustainably managed, the oceans can play a significant part in helping to feed the nine billion people projected to be on earth by 2050 [5].

Accelerating adoption and implementation of robust traceability technology - such as blockchain, a method of securely storing and distributing information [50], has recently been seen as a valuable endeavor in the sector. This has opened doors to opportunities in order to enhance supply chain accountability, reduce illegality and unsustainable social and environmental practices, and reward responsible actors [51]. By securely collecting, storing and distributing data along the seafood supply chain, robust traceability technology systems offer opportunities to increase transparency and accountability. However, implementing digital monitoring systems into global seafood supply chains is no light venture. Today, the seafood industry remains largely an analog sector. The majority of information collected (where it is collected at all) is done so via analog or "paper-based" methods, which includes observer reports, captain's logbooks and other similar mechanisms that have resulted in management challenges [6].

1.0.1 Research Objectives

According to the Food and Agriculture Organization of the United Nation, around a third of the world's fishing companies are pushing past the recommended biological limits. Overfishing not only destroys the marine environment, but threatens the livelihood of billions who depend on fish as protein or as a source of income for catching and selling. The World Wildlife Fund estimates that $36.4 billion USD is generated each year from illegal, unreported and unregulated (IUU) fishing [23, 54, 41]. Although there exist many definitions of a sustainable fishery, the essence of sustainable fishing is *guaranteeing that there will be populations of ocean and freshwater wildlife in the future.* In the 2015 General Assembly, the United Nations specified the three pillars of sustainability: economic development, social development and environmental protection [11]. Like a three-legged stool, we cannot have resilient oceans without acting on all three pillars, which requires us to improve our systems that support data-to-action across economic, environmental, and social issues [10]. At the time of writing this thesis, there have been no known surveys or investigations into the prominent presence of blockchain-based digital monitoring pilots in the seafood sector, despite it's growing popularity as a methodology. As discussed in the previous section, the seafood industry is historically a paper-based sector experiencing a wave of technological innovation due to renewed interest in global fishery regulations and increased feasibility of performing computation at sea through digital monitoring systems [29]. This research is a critical piece in order to understand the current state of blockchain as a digital monitoring methodology in the seafood sector, possibly influencing the future piloted initiatives in the field. In Section 3.3, three case studies illustrate succinctly how blockchain as a methodology is being used in the seafood sector.

The use of machine learning, specifically the field of computer vision, to supplement digital monitoring efforts currently only exist to recognize fishing activity (holding and unloading fish cargo) and object identification (fish presence recognition, fish species identification, fish counting, and feature measurement) [22]. However, these existing electronic monitoring systems hold potential to provide the the infrastructure for much more than commodity detection at sea. In a sector that has experienced devastating infractions in the past decade due to infringement on human rights labor laws and violations of social responsibility efforts at sea, therein lies great opportunity to use machine learning to create safer places for fishermen to work. On a vessel today, 88% of the fishermen who fall off the vessel without a personal floating device, do not survive; a large portion of those deaths are due to unsafe fishing practices, where the fishermen is leaning over to bring aboard the harvest [6]. If these positions are properly identified at sea, effective prevention planning can be put in place while training these fishermen before their next trip on the vessel.

Finally, the geography of this research work is framed such as to be a key resource to the Ministry of Marine Resources of the Cook Islands in their efforts to launch a fleet of digitally equipped longline vessels in the next year. Futhermore, this document aims to live on as a guide to a broader island nation states model, where the country's marine resources hold incredible economic potential if properly regulated.

The objectives of this research are three-fold:

(1) to provide a novel investigation into the best-in-class digital monitoring systems for fisheries conservation and social responsibility to ensure a flow of quality data from

vessels, which can be put into an encrypted distributed ledger to confirm transparency and accountability throughout the supply chain.

(2) to provide a novel proof-of-concept machine learning model for assessing fishermen workplace safety at-sea.

(3) to develop recommendations for policy solutions and technology providers to apply best-in-class systems to the Cook Islands as part of their fisheries reform effort led by Conservation International and partners.

1.1 Thesis Structure

This research seeks to inform upon two inter-related conservation challenges in the fisheries sector: harmful, illegal, and ecological destructive fishing practices and social responsibility challenges, including labor and human rights violations. The review of technologies and in particular digital monitoring systems will focus on these two challenges focusing on systems that can deliver outcomes for:

(1) Social safeguards for workers at sea: including identifying where existing fishing practices can be improved, ensuring that every fisherman that goes out to sea can safely return home.

(2) Environmental best practices: including catch documentation and traceability systems, verification of adherence to regulations regarding harvesting practices to reduce environmental harm and maintenance of ocean ecosystem integrity.

This thesis begins with an in-depth review of digital monitoring as a fisheries management tool through the lens of the Diffusion of Innovation Theory, which is a social science theory that seeks to explain how, why, and at what rate new ideas and technology spread [44]. In this research, the seafood supply chains are analyzed as Roger's social system and robust digital data capture through digital monitoring as the innovation being introduced. The use of distributed ledgers is further investigated as a method of digital recording and the merits of this method being tested by potential adopters are reviewed through a series of case studies. Leveraging machine vision is another way to process captured data at sea. If blockchain is a method of storing and distributing data, machine learning models hold the potential to aid in the automation of an digital monitoring system (e.g. marking specific scenes captured at sea that can later be flagged for review by an observer or auditor).

Chapter 2

A Framework Towards a Digital Sea

2.1 Context

Complex trade paths and a lack of transparency undermine effective fisheries management, putting at risk food security and livelihoods for billions of people. While blockchain has been proposed as a solution that brings about transparency and better understanding of provenance, it remains unknown under what conditions is blockchain an effective solution for improving transparency and accountability for seafood supply chains. An assessment of ten existing blockchain pilots in seafood finds that blockchain is only effective if a robust and accurate digital monitoring system precedes it. As applications of blockchain are only just developing, I assess the trajectory of the current field through the lens of the Diffusion of Innovation Theory. My assessment aims to provide an informed perspective to address the active dialogue regarding the role of digital monitoring (the innovation being diffused) and blockchain (a method of digital monitoring) for traceability in the seafood sector, including the capabilities of the technology, where expectations are being met, and where gaps remain in designing future initiatives to better meet challenges.

Digital monitoring has been defined as "a tool used to collect fishing data including: the number of fish that are caught, fishing effort (e.g., number of hours or days spent fishing) and bycatch."[24]. The advent and adoption of digital technologies, including Vessel Monitoring Systems (VMS), Automatic Identification System (AIS), and Electronic Recording and Reporting Systems (ERS), is slowly transforming the seafood industry. The shift toward electronic technologies is now accelerating, providing opportunities for more robust data-driven management and transparency of production practices and their associated impacts on populations and ecosystems [49]. Examples of new technologies in fisheries include smart weighing at sea, radio-frequency identification (RFID) for tagging and tracking, smartphones and apps for monitoring, artificial intelligence for species recognition and fish counting, drones for high-level fishery assessments, and on-board cameras [13]. Figure 1 illustrates where these technologies potentially exist on a vessel.

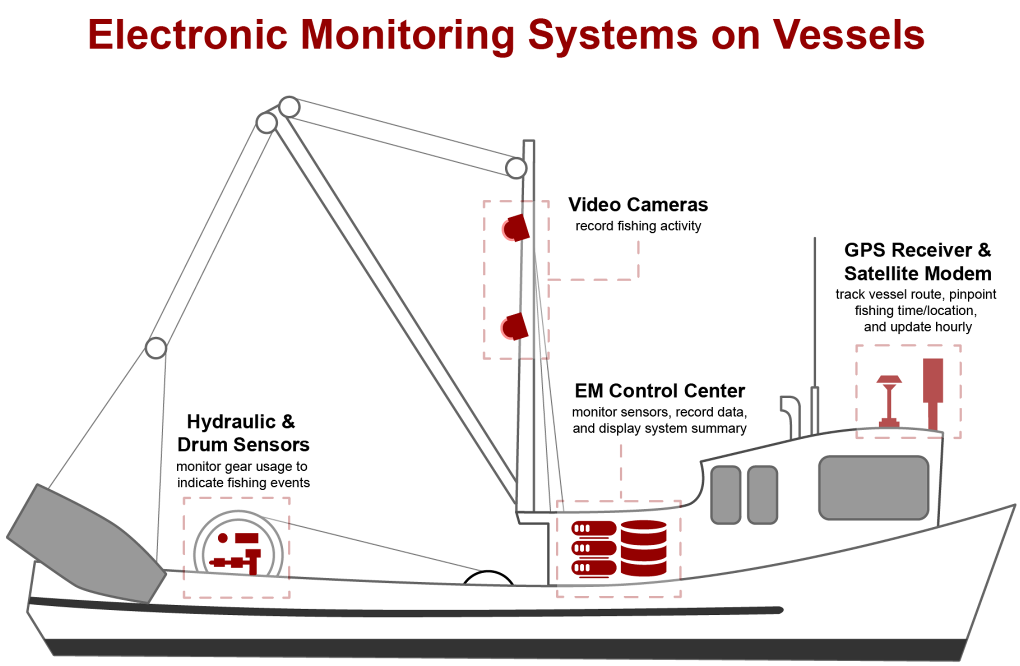

Figure 2-1: Figure 1: Example of digital monitoring Systems on Vessels. (Artwork by Evan Denmark)

As is typical of innovation adoption in industries that are traditionally analog, technologies with greatest traction are those that seem to benefit from a combination of trial and error refinement, policy or regulatory requirements, and cost reduction over time. For example, today digital monitoring is increasingly supplementing the data collected by human observers [38]. This shift has accelerated as costs of digital monitoring technologies, such as camera systems, have slowly dropped and the demand for transparency and data from regulating bodies and markets continues to increase [25]. A promising new area in the digital seafood space is the application of blockchain technologies for seafood traceability. Growing press coverage and academic literature from a diverse array of industries such as manufacturing, transportation, communications, electric/gas and sanitary services, finance, insurance, real estate, public administration and trading reveal cross-cutting excitement around utilizing blockchain technology [27]. Yet, despite the attention, methodologies to reliably store and transmit the products of digital monitoring, such as blockchain, remain novel in the seafood sector. It is a nascent field, with industry supporting the first pilots in 2016, in collaboration with non-governmental organizations (NGOs) and government-partner initiatives[35].

2.1.1 Diffusion of Innovation Theory Towards Ocean Conservation

Prior investigations have applied Everett Roger's Diffusion of innovation theory to analyze patterns of effective intraorganizational and interorganizational conditions that drive conservation intervention strategies [43, 36, 37]. Digital monitoring has the potential to be an effective fisheries management tool, and therefore enable conservation intervention strategies at sea [17]. Diffusion is a process which alters the structure and functioning of social systems by introducing an innovation within a system. An innovation can be an idea, object or practice which is new to the members of the society [45]. In this research, I consider the supply chains of the seafood sector as Roger's social system and robust digital data capture through digital monitoring as the innovation being introduced. Blockchain is a method of digital recording and this investigation will unpack the merits of this method being tested by potential adopters. According to Rogers, adoption of an innovation is determined by five attributes: relative advantage, compatibility, complexity, trialability, and observability [46].

The mechanism for diffusion is the five-stage model of diffusion: (1) Knowledge or

Awareness – where the entity (or decision-making unit) becomes aware of an innovation and has some idea of how it functions, (2) Persuasion or Interest – where the entity forms a favorable or unfavorable attitude toward the innovation, (3) Decision or Evaluation – where the entity engages in activities that lead to a choice to adopt or reject the innovation, (4) Implementation or Trial – where the entity puts an innovation into use, (5) Confirmation or Adoption – where the entity evaluates the results of an innovation-decision already made. In Rogers' 1983 edition of Diffusion of Innovation, he defines diffusion as "the process by which an innovation is communicated through certain channels over time among the members of a social system". As previously mentioned, I consider the seafood sector, and the supply chains within that sector, as one such social system where adopters can be categorized as innovators, early adopters, early majority, late majority and laggards (Rogers, 1983). Since this portion of research focuses on an advanced method of digital monitoring (blockchain) in the pilots, I hereafter categorize the entities behind these pilots as early adopters. In the discussion section, I will walk through the five stages of Rogers' model in order to examine at what stage these fisheries currently are in terms of adopting the innovation of reliable digital monitoring. This approach enables us to properly evaluate the necessary conditions for blockchain to merit adoption by the seafood sector.

2.1.2 Implications for digital monitoring in Seafood

Diffusion of innovation theory holds that the characteristics of an innovation shape the likelihood of adoption [33]. In the context of marine conservation, previous research has shown that key characteristics of an innovation include relative advantage, observability, compatibility, flexibility/low complexity, trialability which "reflect the interplay between innovators, adopters, mode and implementation and broader social-ecological context"[36, 21]. Applying this to the review of nascent blockchain and digital monitoring pilots, the results suggest that adoption will be shaped by the characteristics:

(1) The relative advantage of digital monitoring over traditional analog data capture is perceived to "offer the possibility of better information, better decision-making, and

better fishing"[26].

(2) The observability (the degree to which the results of an innovation are visible to others) of digital monitoring is immediate (e.g. cameras on the working deck of vessels).

(3) Digital monitoring systems in seafood aims to eventually become the replacement of existing analog data recording systems. Therefore compatibility (the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters) [46], is reliant on the design of the digital monitoring system.

(4) Digital monitoring systems in the seafood sector require robust and resilient technological infrastructure to capture real-time data in harsh environments at sea [4], therefore it might have different levels of complexity (the degree to which an innovation is perceived as relatively difficult to understand and use [46]) to initially implement.

(5) The trialability (the degree to which an innovation may be experimented with on a limited basis) of digital monitoring is also potentially high, due to the same reasoning behind high complexity in (4).

In the multi-organizational structures behind these pilots, it was confirmed through the informational interviews that 80% of the pilots did have pre-existing digital monitoring or digital data recording infrastructure before introducing blockchain as a methodology for recording the digital data. Mapping the pilots through the five stages of the diffusion process.

The first stage (awareness/knowledge), the entity attempts to form three types of knowledge: (1) awareness-knowledge, (2) how-to-knowledge, and (3) principles-knowledge[46]. The awareness-knowledge was acquired through global communication efforts focused on electronic data capture in the seafood sector, such as the Global Dialogue on Seafood Traceability [8] and the Seafood Alliance for Legality and Traceability [2] that play a significant role in priming the seafood sector for uptake of digital monitoring technologies. As previously mentioned, the pilots in this survey were a product of multi-organizational partnerships, where the how-to-knowledge (which contains information about how to use an innovation correctly) and the principles-knowledge (which includes the functioning principles describing how and why an innovation works) came from these partnerships. For instance, in every pilot interviewed for this research, there was an entity that identified as a "technology expert" with the knowledge of how to implement the digital monitoring system and understood why it worked, whether or not there was pre-existing infrastructure. Further, for the pilots in this survey that used blockchain as a data recording methodology, there was a "blockchain technology expert" that provided the software as a service.

The second stage of persuasion occurs when the entity develops a negative or positive attitude toward the innovation [46]. As mentioned at length in the methods, all of the interviewed pilots reported driving factors to pursue the advanced methodology of digital recording (blockchain) out of the potential value add of blockchain technology for certain markets and 80% of the pilots reported the pre-existence of digital monitoring technology or digital data recording platforms being utilized in the fishery for governmental auditing, third-party auditing or for adhering to certain certification and standard requirements. In other circumstances, the implementation of blockchain was a facet that the fishery could leap steps in order to put into place digital monitoring where the level of existing infrastructure was low. The decision or evaluation stage is difficult to gather empirical evidence on because of its individualistic nature, however I assume that the mere existence of the pilots signify that the decision to trial the implementation of an advanced digital monitoring methodology (blockchain) confirms that at least "partial-adoption" has been been reached. None of the informational interviews stated that a discontinuance decision (which is to reject an innovation after adopting it earlier) [46] was being considered. A pilot study is defined as "A small-scale test of the methods and procedures to be used on a larger scale" [42], therefore by definition, these pilots are trial implementations of a larger scale initiative to implement advanced digital monitoring techniques. In order to scale past the trial phase into the confirmation or adoption stage of the diffusion process, perceived barriers (Section x.x) must be overcome to prove reproducibility and should be done over a long time series. As an innovation, digital monitoring is a tool that consists of many possible opportunities and applications, therefore digital monitoring is open to reinvention in practice. In this research, I saw the reinvention of digital monitoring from NOAA's classic model for digital monitoring systems (a tool used to collect fishing data including: the number of fish that are caught, fishing effort and bycatch) [24] into a platform for incentivize high-quality data capture by fisher helping farmers in aquaculture meet certification standards and track their employee contracts.

2.2 Overview of Blockchain for Seafood Supply Chains

At its core, blockchain is a method of securely storing and distributing information [50]. A blockchain network creates trust through cryptographic operations that allow all stakeholders to exchange digital data without the use of a middle-party platform, such as a central data storage platform. Currently, there are at least three types of blockchain networks — public blockchains, private blockchains, and consortium blockchains, or "semi-private" blockchains (Figure 3-1). Blockchain is implemented in a range of ways from public ledgers for digital currencies (e.g Bitcoin and Ethereum) to enterprise solutions (e.g Hyperledger's Fabric and Amazon's Blockchain as a Service) [20].

By technical design, a blockchain network is simply a distributed database with verifiable entries that cannot be manipulated once recorded. If built as a public ledger, then all participants have access and contribute to all entries in the ledger. If the blockchain is built as a permissioned ledger, the blockchain network is operated by an administrative actor who can choose to exclude certain stakeholders from viewing entries, making it not fully transparent to all stakeholders. Finally, and perhaps most critically to note: by itself, blockchain technology cannot verify the accuracy or authenticity of the original data entered into the blockchain. These design factors have major implications for the functionality of blockchain as a traceability solution in the seafood sector.

While the excitement surrounding blockchain is high across many sectors [18],

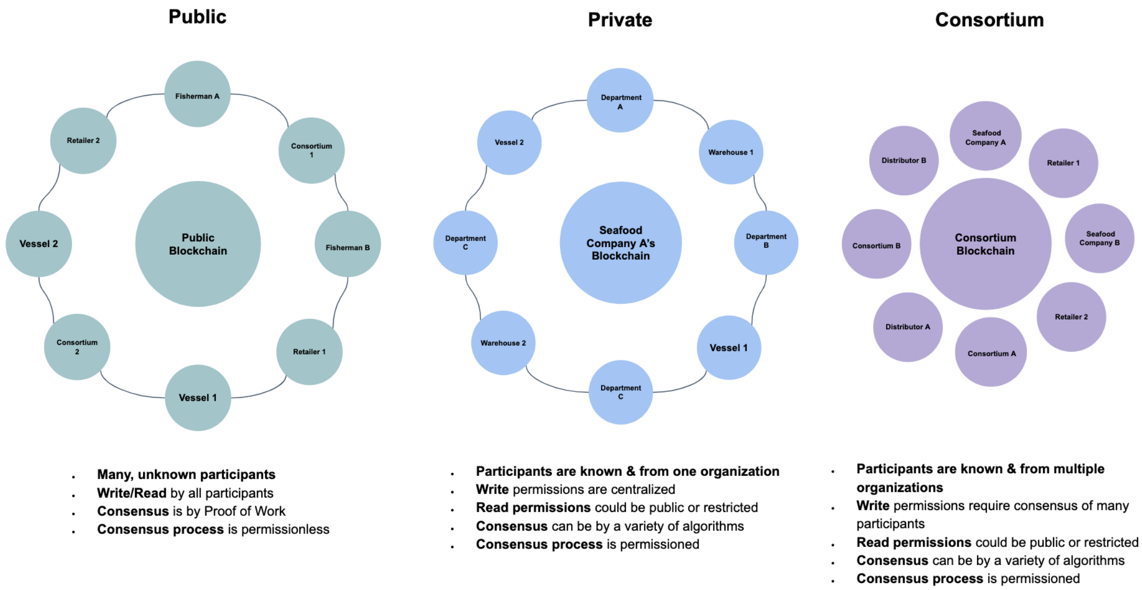

Figure 2-2: High-level Summary of Blockchain Types Consensus (How blocks are added to the chain of blocks (the "blockchain")); Consensus process (the process of writing to a block in the blockchain); Read permissions (the ability to read the data on the blockchain); Immutability (how tamper-proof the data on the blockchain is); Efficiency (how fast you can access the data and how well the blockchain scales up in size to include more data)

there is very little information about the performance of this technology in the seafood sector. To effectively harness the potential of blockchain to support legal, trustworthy, and responsible seafood, the sector must understand what is working and not working in blockchain's application within the seafood trade. In the following section, I assess the current landscape of nascent seafood advanced digital monitoring pilots using blockchain to understand the drivers, barriers and steps taken to overcome barriers behind these initiatives.

Chapter 3

Blockchain and Fisheries: The Good, The Bad, and the Yet-to-Be-Proven

3.1 The Role of Blockchain Technology for Seafood Traceability

As of the writing of this thesis, a technical investigation of the landscape of distributed ledger technology use in the seafood sector is not known to previously exist. Even though, as the following sections will illustrate, blockchain pilots in the seafood sector continue to exponentially multiply, confirming the perceived usefulness of blockchain for the sector. For instance, one specific pilot [1] was completed during the editorial review of this paper. Over the past four years, ten blockchain-based pilot projects have launched as seen in Table 3-1: one in 2016 [2], five in 2018 [3] [4] [5] [6] [7], and another four in 2019 [8] [9] [10] [11]. These pilots provide the first opportunity to assess the necessary

[1] IBM Food Trust, Raw Seafoods
[2] Provenance
[3] Atato, Parties of the Nauri Agreement (PNA), Pacifical Tuna
[4] SeaBOS
[5] ConcenSys, Viant, WWF-New Zealand
[6] Fishcoin
[7] OpenSC, WWF-Australia
[8] SAP, Bumble Bee Seafoods
[9] Diginex, Verifik8
[10] National Fisheries Institute (NFI), Seafood Industry Research Fund (SIRF), IBM Food Trust
[11] IBM Food Trust, Raw Seafoods

conditions (e.g. previous investing leaps towards reliable digital data capture) and the performance of this digital monitoring methodology - through such assessment, I can identify strategies and best practices to guide development of subsequent pilots and investments in such initiatives.

3.1.1 Methodology

In order to better understand the landscape and conditions surrounding the launch, successes, and barriers these pilots faced, I conducted informational interviews with key informants from 8 of 10 currently existing pilots, summarized in Table 1 (Two pilots did not respond to multiple interview requests from the authors, and those are noted in Table 1). The table summary also contains details from the investigational survey of peer-reviewed and grey literature completed from February 2019 through February 2020, including: (1) interviews with key correspondents from the blockchain technology implementation side of the pilot (8/10 pilots); (2) a technical review of the technologies used during the pilot, including databases, and demos when available; (3) a surveyed review of all available documents, press information, and other technical information that was made available during the informational interview; (4) three case studies of the pilots that aim to bring the reader deeper understanding of the three main motivations to use blockchain for enhanced digital monitoring.

The main focus of the interviews was to better understand the technical depth, successes, and barriers faced during the lifespan of these pilots from an internal perspective. The criteria used to define the population of the ten pilots was dependent on existence (did the pilot have a start/end date in 2019) and relevance to this research (was blockchain used as a fundamental technology in the pilot). Interviewees were reached out to via email with an interview request and the questionnaire utilized in the informational interview is available to the reader in the Supplemental Information section. The interviewees from the pilots were selected based on availability and relevance to the blockchain implementation portion of the pilot. When a technical representative from a pilot was not available for interviewing, I spoke to the individual who either managed the project or identified as a representative who could speak at

Interview Method	Interviewee Affiliation	Blockchain Technology Facilitators	Other Project Facilitators	Blockchain Type	Blockchain Platform	Pilot Launch Date	Commodity Target	Operating Geography	Pilot Objective
Phone Interview	Atato	Atato	Pacifical, Parties of the Nauri Agreement (PNA)	Public	Ethereum	August 2018	Tuna (Skipjack, Big Eye, Yellowfin)	Pacific Islands	Increase consumer confidence through digital tracking of Pacifical tuna using smart contracts on Ethereum's main network
Phone Interview	Systems, Applications, and Products (SAP)	Systems, Applications, and Products (SAP)	Bumble Bee Seafoods	Permissioned	SAP, Multi-chain	March 2019	Tuna (Yellowfin)	Indonesia	Increase consumer confidence through digital tracking of yellowfin tuna using multi-chain
Phone Interview	Nutreco	IBM Hyperledger Fabric	Seafood Business for Ocean Stewardship Council (SeaBOS)	Permissioned	Hyperledger Fabric	December 2018	Sardines	Mexico	Increase consumer confidence through digital tracking of sardines using Hyperledger Fabric
Virtual Meeting Interview	TraSeable	Treum (Formerly Viant), TraSeable	Fiji Sea Quest, WWF-New Zealand	Hybrid	Ethereum	January 2018	Tuna	Australia	Increase consumer confidence through digital tracking of Tuna using Hyperledger Fabric
Virtual Meeting Interview	Fishcoin	Fishcoin	Eachmile Technologies and Kolega Fisheries	Permissioned	Stellar	September 2018	Western King Prawn fishery	Spencer Gulf	Incentivize high quality data capture by fisher using utility tokens (Fishcoin) on Stellar
Virtual Meeting Interview	Provenance	Provenance	International Pole and Line Foundation (IPNLF), Humanity United	Hybrid	Ethereum	May 2016	Tuna (Skipjack)	Phuket, Thailand	Increase consumer confidence through digital tracking of tuna using a side-chain of Ethereum.
No Interview; No response to author's outreach efforts	*Not Available*	*Open Supply Chain (OpenSC)*	*WWF-Australia, BCG Digital Ventures*	*Permissioned*	*OpenSC*	*Spring 2018*	*Patagonian toothfish*	*Southern Thailand*	*Increase consumer confidence through digital tracking of Patagonian toothfish using OpenSC*
Virtual Meeting Interview	Diginex, VerifiK8	Diginex	VerifiK8, Mekong Club	Permissioned	Diginex	January 2019	Shrimp	Phang-na, Thailand	Help farmers in aquaculture to meet certification standards and track their employee contracts using a side-chain of Ethereum.
No Interview; No response to author's outreach efforts	*Not Available*	*IBM Hyperledger Fabric*	*IBM Food Trust, National Fisheries Institute (NFI), Seafood Industry Research Fund (SIRF)*	*Permissioned*	*Hyperledger Fabric*	*July 2019*	*Multi-Species*	*Not Available*	*Increase consumer confidence through digital tracking of seafood using Hyperledger Fabric*
Virtual Meeting Interview	Raw Seafoods Inc	IBM Hyperledger Fabric	Raw Seafoods Inc, Marel Service Solutions, Producers Market's StoryBird Solution	Permissioned	Hyperledger Fabric	Spring 2019	Scallops	New England	Increase consumer confidence through digital tracking of scallops using Hyperledger Fabric

Figure 3-1: Summary of Blockchain Pilots

depth towards the technical portion of the pilot. Since the majority of the pilots were a multi-organizational effort, the affiliation of the interviewee is available in Table 1 for full transparency. Prior to the interview, background research was conducted and included a comprehensive review of available grey literature, including both academic and popular media channels. A list of the literature and documentation that was reviewed per the respective pilot is available for the reader in the Supplemental Materials.

Based on the information I gathered through this survey approach, I conducted an analysis of the data grounded in Roger's diffusion stages and Beal and Bohen's diffusion process theory [16] to identify key insights into the primary research question: under which conditions is blockchain an adoptable solution for recording digital data for seafood supply chains? In order to address this question, we must first step back and acknowledge that the innovation that is being diffused in the seafood sector is robust, accurate and real-time digital data capture. Blockchain is simply a method of recording the captured digital data and the pilots in this survey are the potential adopters of this technology, where the interest in the potential value add of blockchain for certain markets was the main driver of the pilots. In the discussion portion of this piece, I investigate each of the following stages of diffusion at length: (1) Awareness/Knowledge, which provide a framework for the initial factors that led to a pilot launch, including, (2) Interest/Persuasion, which provide a framework to understand how the entities initially gathered interest in digital monitoring. I discuss the (3) Decision/Evaluation stage, which was the process of weighing advantages and disadvantages of pursuing the pilot, which Roger noted to be the most difficult stage in which to acquire empirical evidence due to the individualistic nature of this stage [46]. Finally, the (4) Trial stage, which is characterized "by small-scale, experimental use" [44] of the innovation enables the entity to determine if the (5) Adoption stage can be pursued. The adoption stage is the final stage of diffusion, "characterized by large-scale, continued use of the idea, and most of all, by satisfaction with the idea" [16]. Because I surveyed only pilots in this research, I will focus on the first four stages listed above.

3.2 Results

3.2.1 Pilot Landscape

Table 1 is a high-level extrapolation of the data that was gathered from each interview, which includes the Blockchain Technology Facilitators (the entity who identified as implementing the blockchain protocols), Other Project Facilitators (the other entities who associate themselves with the pilot), Blockchain Type (permissioned, consortium or public), Blockchain Platform (the blockchain network), Pilot Launch Date, Commodity Target, Operating Geography, and Pilot Objective (a one-sentence summary of the pilot's objective). According to the research findings, most pilots were developed in the Pacific and in Southeast Asia. Pilots primarily focused on high-value fisheries, such as tuna seen in Table 3-1. Other operating geographies included Mexico and New England, where other fisheries such as sardines and scallops were the focus. The number of vessels included in these pilots ranged from one to 50 vessels and depended on the pilot. Out of the ten pilots observed, only one of the pilots used a public blockchain model. This design choice enabled them to show their data to all stakeholders throughout the supply chain, regardless of affiliation. The rest of the pilots fall under the category of permissioned or consortium blockchains models, as private or semi-private blockchain networks which is further explained in Figure 2.2. In the following three subsections, I walk the reader through the foundations of the Knowledge/Awareness and Interest/Persuasion stages of diffusion through the drivers, enabling conditions and perceived barriers of the surveyed pilots through the perspective of the case studies.

3.2.2 Drivers

As mentioned in the Methods section, three case studies were completed as part of this research. These case studies consisted of a deep investigation into the respective pilots together with the main pilot representative(s) or interviewee(s). These case studies were selected to represent the three primary which encompass the core objective of the pilots: (1) to help farmers in aquaculture meet certification standards and track their employee contracts (social responsibility), (2) to increase consumer buying confidence through the tracking of seafood from "bait to plate" (product provenance) and (3) to create a data marketplace for fishermen by incentivizing high-quality data capture (tokenization of data to incentivize high-quality data capture). All ten of the pilots can be categorized somewhere within these three objectives, although the majority (80%) identified as belonging to the second category - targeting product provenance to increase consumer confidence. Through these case studies, I analyzed the motivations, typical barriers and steps taken to address those barriers within each pilot. Further, these case studies allow for deeper investigation into the relative merits of blockchain as a method for enhanced electronic monitoring in fisheries.

Pilot	Objective	Target End User	Initial Barriers	Steps Taken to Address Barriers	Pre-Existing Digital Monitoring System
VerifiK8/Diginex	Increase safety in laborer workplace	Aquaculture farm laborers, Government auditors	Mistrust and fear surrounding the technology	Enhanced communication efforts with the laborers and managerial staff	VerifiK8's existing farming monitoring tool, a web and mobile application
Raw Seafoods/IBM Food Trust	Increase consumer confidence	Scallop consumers	Ineffective digital strategy from retailers and resistance from other entities in the supply chain	Sharing "success stories" of year-over-year margin increase with various entities in the supply chain	Scallop industry's stringent requirements for data recording on Nordic Inc's vessels
Eachmile Technologies	Incentivize high-quality data capture and create a data marketplace	Fishermen	High cost of sustained use and development of the platform	Technological design decisions were made to lessen the cost (e.g moved from Ethereum to Stellar blockchain)	Eachmile's existing browser-based application (mFish)

Figure 3-2: Summary of Case Studies

Although the case studies and interviews cannot be absolute proxies for each individual pilot because each pilot in this landscape assessment is intrinsically unique, there are recognizable patterns I gathered from the case studies that serve as insightful guideposts as I seek to frame the uptake of the innovation (digital monitoring). Following that, I examine the merits of the specific digital monitoring methodology (blockchain) that was trialed in seafood sector supply chains.

3.2.3 Enabling Conditions

Three critical patterns emerged from the ten surveyed pilots as indicative enabling conditions: (1) a multi-organizational partnership formation (between a technology service provider and fishery/vessel owner or aquaculture farm), (2) a form of short-term launch-funding (from either a partnering organization, a nongovernmental organizations or a governing body) and (3) a pre-existing pipeline of digital capture technology. At least 87.5% of the interviewed pilots [12] [13] [14] [15] [16] [17] [18]specifically referenced technology partners that had paved the foundations of necessary information technology infrastructure on the vessels or on the aquaculture farm preceding the launch of the blockchain pilot and all interviewed pilots remarked that these three conditions were crucial to the successful uptake of blockchain technology for data management. the review of the financial models for these pilots was from the informational interview, and therefore was cursory. Through the informational interviews, it was understood that the pilots were not able to or did not prioritize the development of a business model for integrating blockchain into the digital monitoring pipeline that would ensure long-term use or scaling past the trial phase. However, several initiatives did note that they plan to continue working to integrate these technologies into their existing business models.

3.2.4 Perceived Barriers and Successes

I now turn to the three case studies to inform upon the barriers generally seen in the three classic objectives or uses of blockchain as a methodology for digital recording (social responsibility, product provenance, and incentivizing quality data capture). As mentioned previously, these case studies are not considered as a one-size fits all, but simply provide a lens to look through when discussing the uptake of technological innovation (digital recording) and a specific method of that innovation (blockchain).

[12] Atato, Parties of the Nauri Agreement (PNA), Pacifical Tuna
[13] SeaBOS
[14] ConcenSys, Viant, WWF-New Zealand
[15] Fishcoin
[16] OpenSC, WWF-Australia
[17] SAP, Bumble Bee Seafoods
[18] Diginex, Verifik8

3.3 Case Studies

3.3.1 Case Study A: Shrimp aquaculture in Thailand

The pilot's duration was one year, beginning January 2019 and finalizing in January 2020. The target industry was shrimp aquaculture farming in Phang-nga, Thailand. The pilot was funded through a string of NGO and government grants. Diginex and NGO Mekong Club first initiated the blockchain-enabled eMin project, and VerifiK8 was later asked to contribute with their experience of already working with aquaculture farms in Thailand. eMin pre-dated the blockchain pilot and was an existing farming monitoring tool. The interface was a web and mobile application that helped farmers in agriculture or aquaculture to meet certification standards, and was already being used by thousands of workers on the ground in Thailand. The pilot experienced two main challenges, and both of these challenges arose during the implementation of the technology: (1) a fear from farm managers that "too much transparency could lead to an NGO (non governmental organization) pointing out issues and raising too much awareness" and (2) workers not inherently trusting the technology, creating "fear [of] what people will do with their personal documents." These quotes come from the co-authored case study completed with a representative from VerifiK8 and Diginex and can be found in the supplemental materials section of this paper.Both challenges were rooted in the absence of onboarding or traditional "human resources department" infrastructure. This made technology user training and onboarding very difficult to do effectively at scale, leaving large gaps in knowledge between managers and trainee groups. The knowledge gaps created space for fear and friction. Steps taken to address these barriers were measures that increased effective communication to the laborers that they are the owners of their documents. Similarly, the managers were encouraged to adopt the technology with a tangible story from a positive point of view: if you increase transparency, you show your willingness to cooperate, and therefore avoid social risks. A noteworthy success has been the active user count of the technology through the pilot stage, now at over 5,000 users and growing. It is suspected that this success is mainly due to the adoption process being driven by the laborer and not the managerial authorities, since ultimately, the platform known as eMin, is built for the laborer to have access to documentation they perceive as important for their livelihoods [12].

3.3.2 Case Study B: New England scallop fishery

The pilot's duration was six months, beginning in November 2018 and finalizing in Summer 2019 on a single vessel. During the informational interview, it was said that this pilot plans to continue through the 2020 scalloping season. The target fishery was wild caught sea scallops in New England. This fishery was selected because the scallop fishery was already heavily regulated thanks to an anemic harvest that scared the industry into an awakening in 1998 due to overfishing [31]. Since 2001, the Atlantic sea scallop industry has made an incredible recovery due to strict management measures and adherence to independent certifications such as the Marine Stewardship Council Fisheries Standards. Essentially, it was not a cumbersome lift to transfer the data that had already been meticulously collected for regulation purposes over the past two decades onto an immutable ledger. From the informational interview, it was gathered that the pilot experienced two main challenges, and both of these challenges arose from lack of strategic initiative and general unwillingness from other entities in the seafood supply chain to adopt novel technology. (1) The first challenge originated in lack of retailer digital strategy; vendors were unable or did not have the bandwidth to communicate effectively to the consumers with the immutable data they now had access to. (2) The second challenge broadened out to a more systemic issue; the retail and food-service levels of the seafood industry are resistive to the idea that there is value in using blockchain technology to prove provenance of their product. In response to the former claim, it was mentioned that over the course of the pilot, the food-service retailers that leveraged the data effectively, were rewarded with a 38% increase year over year in sales in scallop entrees sold during the test period from November 2018 through late November 2019. This margin of sales increase has been sufficient for justifying the pilot to scale beyond its current stages, which Raw Seafoods plans to continue spearheading with the IBM Food Trust and with Producers

Market "StoryBird" solution.

3.3.3 Case Study C: Spencer Gulf King Prawn fishery

The pilot began in March 2019 and completed in April 2019. The pilot target fishery was the Western King Prawn fishery of the Spencer Gulf along the coast of South Australia to Singapore. For this particular pilot, Eachmile Technologies partnered with Kolega Fisheries, using the browser-based application, mFish and keeping Fishcoin tokens as the digital token used on the platform. The pilot was self-funded and completed with the use of the company's two prawn vessels. Kolega Fisheries are members of the Spencer Gulf and West Coast Prawn Fishermen's Association - and already had data collecting infrastructure in place as a result of their Marine Stewardship Council certification for sustainability [21]. The informational interview revealed that the main challenge this pilot experienced was associated with the cost of sustained use and development of the platform. Certain technological design decisions were made in order to account for these costs. For instance, Eachmile Technologies swapped the underlying blockchain platform from Ethereum to Stellar in order to avoid the high transaction fees (called "gas" on the Ethereum main network) and lower transaction speeds that become prohibitively expensive for the micro-transactions associated with developing nation fishers. Surviving past the Initial Coin Offering (ICO) debacle in 2018 was considered a genuine success and allowed for the building of the android and iOS application along with the browser based application. These interfaces to the technology have allowed the transition of data from a single fisher or farmer on a phone to a permissioned employee of a company. Douglas also mentioned that the pilot's success was also enabled by having an accessible system whereby digital tokens are able to be purchased with a credit card or PayPal account and are redeemable with over 550 mobile operators in more than 150 countries.

Chapter 4

TransparenSea: Computer Vision for Fishermen Safety at Sea

4.1 Computer Vision 101

The history of computer vision begins on July 7, 1966 with a summer project launched by two cornerstone figures of the MIT Media Lab - Seymour Papert and Marvin Minsky. The *Summer Vision Project* was conceived and became the first documented "attempt to effectively construct a part of a visual system" in the pursuit of pattern recognition [48]. The experiment entailed attaching a camera to a computer such that the machine could divide a vidisector picture into regions such as "likely objects, likely background areas and chaos". This seedling of a project opened the floodgates in the early 1970s which enabled formation of the primary foundations that make up the computer vision algorithms that exist today, including image edge extraction, line labeling, non-polyhedral and polyhedral modeling, object representation within larger contexts, optical flow and motion estimation[52].

This thrust of research leans heavily on a particular machine learning algorithm that is considered to be the most effective methodology for pixel classification today - Convolutional Neural Networks(CNNs). In 2012, a large, deep convolutional neural network was used to classify 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes[32]. Mask R-CNN (Regional

Convolutional Neural Network) has been the state-of-the-art model for object instance segmentation since it was proposed by in 2017 [28]. Current instance segmentation methods placed into two categories: one is detection based methods and the other is segmentation based methods. Detection based methods exploit the state-of-the-art detectors, such as Faster R-CNN [33], R-FCN [8], to get the region of each instance, and then predict the mask for each region.

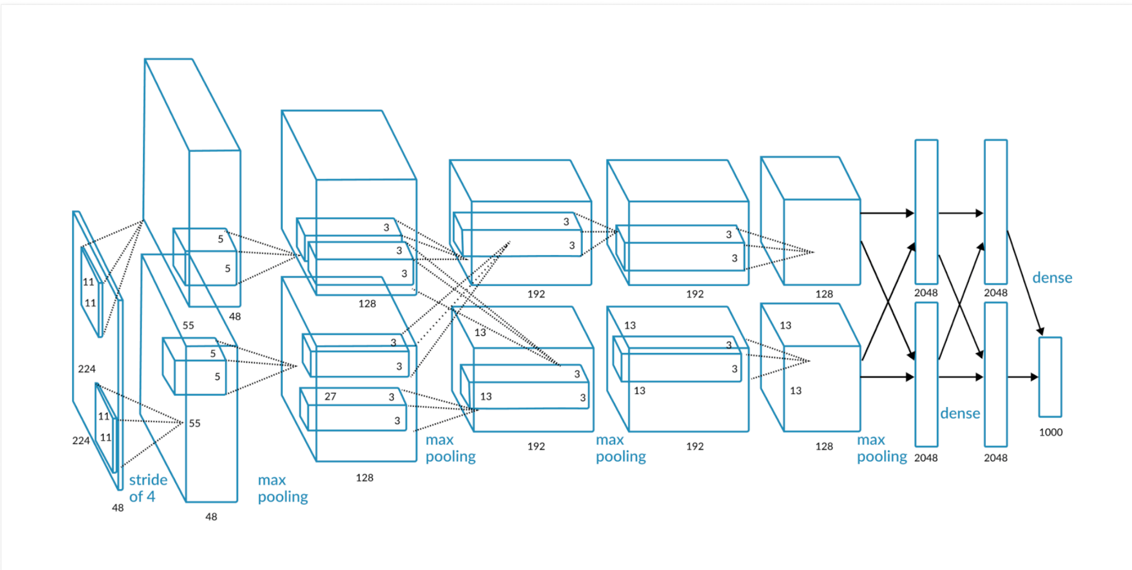

Figure 4-1: The architecture of AlexNet's CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers.[32]

Since the release of this work, CNNs have become the gold standard for image classification.

The system implemented for this research thrust builds upon MASK R-CNN architecture, which is a deep learning algorithm with a Feature Pyramid Network (FPN) and ResNet101 backbone [9]. Feature pyramids are a basic component in recognition systems for detecting objects at different scales. A top-down architecture with lateral connections is developed for building high-level semantic feature maps at all scales. This architecture shows significant improvement as a generic feature extractor in several applications [34].

4.2 Proof of Concept System Overview

4.2.1 Approach

Commercial fishing remains one of the most dangerous jobs in the nation, with a fatality rate that is 23 times higher than for all other workers[3]. The large majority of these fatalities occur due to fishermen putting their bodies over the edge of the vessel when grasping for the longline, or in an attempt to bring onboard a portion of their catch. Fall protection systems such as safety lines and guardrails are often absent because they might interfere with the work or introduce new hazards [39]. With their upper bodies over the edge of the vessel, it does not take much more than a hefty wave to destabilize their grip and send them over the side of the vessel and into the ocean. During 2000–2016, 204 commercial fishermen died from unintentional falls overboard. [19]. Among 83 witnessed falls, 22 victims were recovered but not resuscitated. In order to increase awareness of safe fishing practices on vessels at sea, unsafe fishing practices that are generated out of habit must first be identified (Case, 2018). TransparenSea is an AI system that uses existing video streams of electronic monitoring data from a tuna longline vessel to identify fishing practices on the operation deck at sea to compute how "safe or unsafe" certain fishermen are poised while on duty. Using instance segmentation through a convolutional neural network for multi-object detection and classification (He et al, 2018), I can better understand if fishermen do indeed tend to place their upper bodies or appendices over the threshold of the vessel while gathering the harvest from the longline, putting themselves at greater risk of falling overboard. Ultimately, TransparenSea aims to identify where existing fishing practices can be improved, ensuring that every fisherman that goes out to sea will safely return home.

4.2.2 Formulation

There are two potential solutions to preventing over-board fatalities at sea. An obvious first solution is to simply require all fishermen to wear personal flotation devices (PFD)

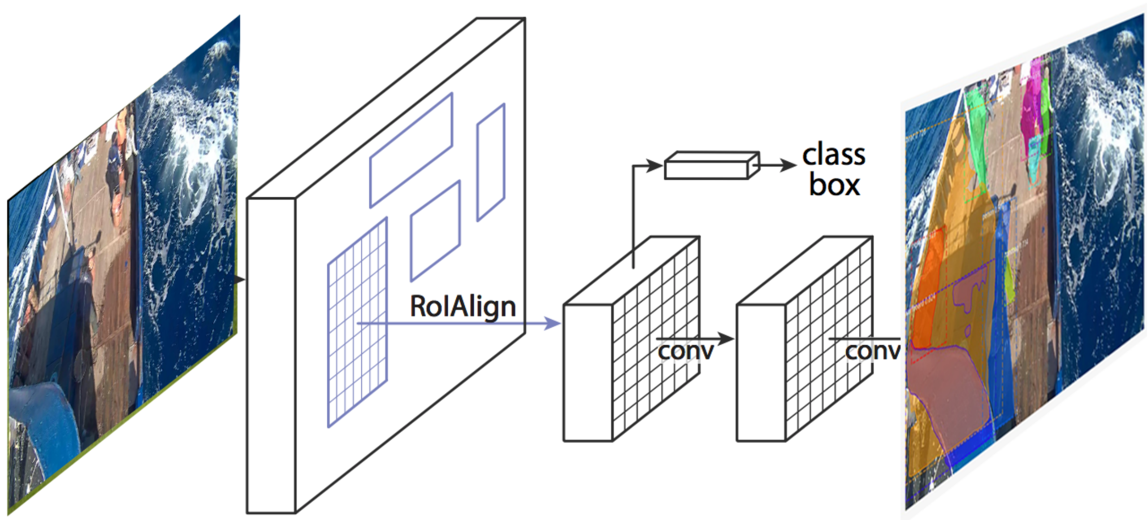

Figure 4-2: Overview Mask R-CNN for instance segmentation on electronic monitoring data

while working on the operation deck. Recent NIOSH (The National Institute for Occupational Safety and Health) data show that many fishermen are not wearing personal flotation devices (PFDs) when they fall overboard or are forced to abandon sinking or capsized vessels. These data clearly show that PFDs greatly increase the chances of survival for these fishermen: 63% of fishermen wearing PFDs when they jumped or fell into the water survived, whereas only 12% of those without PFDs survived [14]. However, many commercial fishermen say that they are unwilling to wear a PFD during routine work on deck because it might interfere with their performance. Although USCG regulations require commercial fishing vessels to be equipped with at least one USCG-approved PFD or immersion suit of the proper size for each person on board, the PFD is not required to be worn [1]. A second possible strategy to preventing these types of fatalities at sea is to behavioral retraining of the fishermen themselves. Before departure to sea, fishermen could be given work safety training that emphasizes how dangerous leaning over the edge of the vessel can be. However, in order to break a habit, one must first become aware of its existence. TransparenSea is a computer vision model that detects humans in a scene that are close to the vessel's edge in order to flag the particular human instance as "dangerous" or "not dangerous" in the scene for post-voyage auditing. By detecting at-risk fishermen through pre-existing electronic monitoring infrastructure, an auditor can review data collected at sea and create intervention strategy plans to ensure safer fishing practices on future fishing voyages.

4.3 Methodology

4.3.1 Modeling Approach

In order to create a baseline data set, over 7,000 images of fishermen at sea were manually annotated as being in positions that were "dangerous" or "safe". The images were pre-localized with bounding boxes around objects of interest (e.g. fish, human) from a dataset of on-board monitoring cameras. These images were composed entirely of long line tuna fishing activity in the Western and Central Pacific with localization's manually drawn by professional annotators to ensure consistency [53]. The dataset was compiled by The Nature Conservancy in partnership with Satlink, Archipelago Marine Research, the Pacific Community, the Solomon Islands Ministry of Fisheries and Marine Resources, the Australia Fisheries Management Authority, and the governments of New Caledonia and Palau.

An Amazon Web Service ec2 p2.8xlarge instance provided an environment to run the Mask-RCNN library with CUDA 10.0, Tensorflow 15.0, Tensorflow-GPU 15.0, Keras 2.0.8. The initial experiment began with a 90-10 split of training and validation data, however after a series of iterations, a 66-33 split of the dataset was implemented. Training began with initial transferred weights from COCO, with a 0.001 learning rate, containing batch sizes of 1000 and 5 epochs.

4.3.2 Instance Segmentation and Transfer Learning

Transfer learning is a technique in which a model developed for a task is applied to a similar second task. This means the stored knowledge gained while solving one problem can be applied to a different but related problem. For example, knowledge gained identifying canoes could apply when identifying boats. The approach has

Figure 4-3: The result of using YOLO's model weights on training imagery

proven to be popular in deep learning models where pre-trained models are used as a starting point on computer vision tasks given the large amount of data and time required to train neural network models from scratch, with transfer learning I have found ways to circumvent the resource use successfully and thus the popularity. However, transfer learning only works in deep learning if the model features learnt are general. Therefore, the layer that is retrained by the new data from task two needs to be optimized by changing the depth up to the point where features have become generalized.

In the model, fishermen are identified depending on their distance from the vessel's edge as dangerous or safe. These are the two new object classifications that will be created and selected for. The trained mask (recurrent convolutional nueral network) RCNN model, is an instant segmentation convolutional neural network that is trained on 80 different objects and can identify humans very well as one of the objects it has been trained to identify. Therefore, using transfer learning the human identification general features can be used to identify the fishermen. An instant segmentation model was used to ensure all vessel fishermen were individually selected to ensure

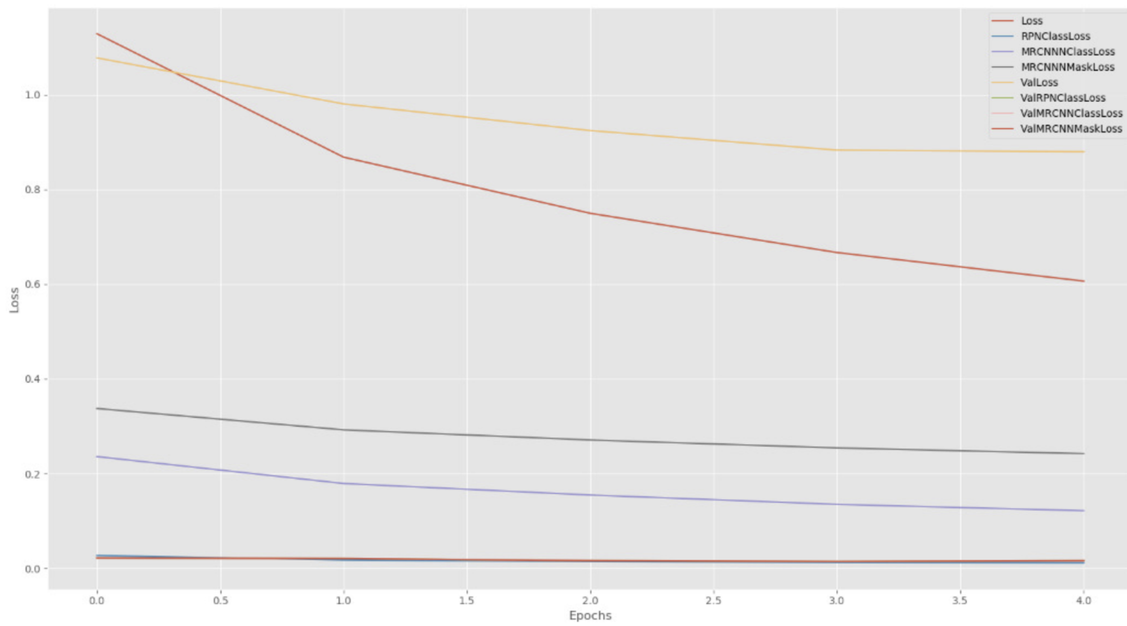

Figure 4-4: Observing how training and test loss change and eventually plateau across epochs

the model would be more robust than a model that looks at all fishermen grouped together as one entity. The vessel fisherman data is then used to retrain the imported neural network weights to ensure proper classification between dangerous versus safe fishermen positioning.

4.3.3 Evaluation

Discussion and Results

Typically, models are trained with a large number of images for a robust performance results. For instance, *Imagenet* is trained with over 14 million images, whereas the dataset that formed the foundations of this work have been manually annotated and on the order of thousands of images. Fortunately, there are other trained models with much larger datasets, therefore through transfer learning from the COCO dataset, the initial weights were to included to provide a baseline model. By leveraging the models trained with larger datasets in our context, I achieved higher precision accuracy results than a model trained on our annotated images only.

The mean Average Precision (mAP) for the classifier was 0.753, tested over as

Epoch	Time	L_{mask}	$L_{RPN\ Class}$	$L_{MRCNN\ Class}$	$L_{MRCNN\ Mask}$	$L_{Validation}$
1	1631s	1.1284	0.0273	0.2360	0.3375	1.0774
2	1444s	0.8679	0.0178	0.1792	0.2924	0.9802
3	1445s	0.7494	0.0144	0.1549	0.2710	0.9240
4	1444s	0.6666	0.0129	0.1352	0.2543	0.8827
5	1445s	0.6063	0.0117	0.1218	0.2422	0.8794

Figure 4-5: Train and test loss change across epochs. The mean average precision (mAP) for the classifier was 0.753

a higher precision would've relayed that more accuracy was achieved, there exists variability due to potential inconsistencies of the labeling by three different people as well as there being a disproportionate number of "safe" labels compared to "dangerous" labels. It is also possible that the mAP could have increased with more epochs and maybe varying the batchsize.

Figure 4-6: Example of masking layer on validation data where the two humans on the edge of the boat were labeled as in danger and the other two as safe

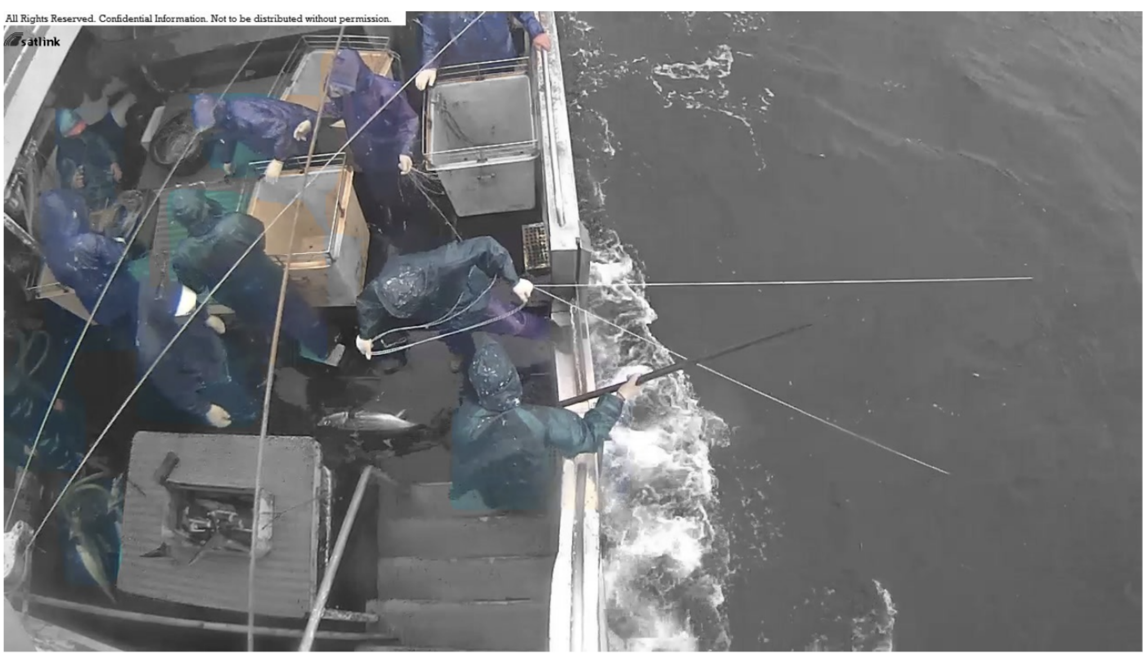

Figure 4-7: Example of masking layer on validation data where all humans in the scene were labeled as safe

Chapter 5

Lessons Learned and Implications for Practice

5.1 Blockchain Secures Data, but Requires Robust Electronic Documentation and Traceability (eCDT)

Blockchain has distinct advantages in securing digitally captured information, but this heightened security advantage requires the initial infrastructure of robust, digital data capture systems. The "Garbage in, Garbage Out" phenomenon poses a real threat to the integrity of these initiatives and here is why. [40].

Blockchain functions as an immutable timestamp, requiring a digital data stream that can be protected once the data is on the ledger. If accurate, verifiable data is entered into the first node of the supply chain through the pre-existing digital monitoring infrastructure, then blockchain can provide increased levels of data security and integrity. If the data entered is inaccurate, the blockchain just locks in that poor quality information. EM technologies can help with providing accurate, verifiable data into a blockchain; but for many fisheries in the world, the systems and processes to guarantee accurate reporting of catch are missing; thus, data entered into an associated blockchain would be suspect.

But, when aligned with robust data entry systems, blockchain can boost security

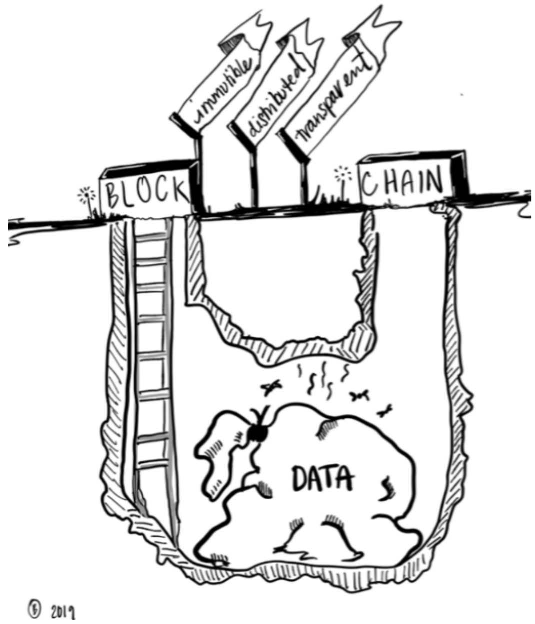

Figure 5-1: *Garbage In, Garbage Out* phenomenon. Garbage data on an immutable ledger is like a secured bunker full of trash.

of the data because it secures data in a distributed, encrypted ledger. Rather than having one central administrator that acts as a gatekeeper to data—a list of digital transactions—the ledger is shared and therefore designed to allow utilization by a range of actors who can access a network of synchronized, replicated databases. This makes blockchain an excellent instrument for preventing tampering with recorded data, because changing data in one database would be easily detected by the non-conformity compared with the other databases. Having increased protection of data integrity is a clear benefit of blockchain, and can insinuate security of information that serves to inform regulators interested in monitoring and adhering to sustainability commitments. However, in order for this distributed data structure to work, the information must be captured and shared digitally for relevant decision-making and analyses that are impacting our oceans today.

5.1.1 Blockchains are Adaptable Structures

Blockchains are systems for recording digital data and as a result they are malleable to the needs of the user, as demonstrated by our functionally diverse array of case studies. Understandably, blockchain-forward pilots are sensitive to the data that stakeholders in the supply chain are willing and unwilling to share with the general public. For instance, in a business-to-business (B2B) relationship there may be proprietary information that the respective businesses will not want or to make public because doing so will put them at a competitive disadvantage. Therefore, we surmise that some data on the blockchain could be public (e.g. required permitting and standards-abiding documentation), whereas proprietary information (e.g., prices, tonnage, specific harvest geography) could remain private, depending on the constraints of the business and transactions. A method exemplified by NOAA's Seafood Import Monitoring Program (SIMP), requires businesses to provide data to the regulator, the National Marine Fisheries Services (NMFS), but the data provided is not made public. SIMP is a " risk-based traceability program requiring the U.S. importer of record to provide and report key data—from the point of harvest to the point of entry into U.S. commerce—on thirteen imported fish and fish products identified as vulnerable to illegal, unreported, and unregulated fishing and/or seafood fraud." [29] Following this model, we see a path forward for future blockchain-forward systems in the seafood sector to provide the framework where all data is collected for regulatory auditing, but certain portions remain proprietary and therefore are not made public. To avoid falling into the common tropes of over-promising blockchain as a technological solution, one must state clearly what information is available. Blockchain-based systems for supply chains have a history of being promoted as a panacea [7], and the seafood sector is no exception to becoming numb to misleading information. Such underserved hype comes at a severe cost - not only in the form of losses by stakeholders in projects, but in their inability to pursue alternative designs and find more productive, effective and profitable opportunities. As an effective methodology for recording and distributing access to digital monitoring data, it is important to recognize where blockchain can deliver on its potential.

5.1.2 Implications for Future Initiatives

Given that resources for advancing sustainable seafood as a whole are limited, I believe it is important to consider how investments in digital monitoring can be maximized for the highest levels of impact. From this body of research, in order to put advanced digital monitoring methodologies (such as blockchain and computer vision applications) into practice, it is beneficial to leverage key enabling conditions (listed in section 3.3), including a multi-organizational partnership formation, short-term launch funding, and investment in digital data capture technology. Other interesting lessons learned from the use cases were that there exists a need to build a sense of trust among those who are being ask to provide data (Case Study A). The challenge of costs to sustain use and development of a data capture interface was seen in Case Study C. Finally, Case Study B demonstrated that building a value proposition is an important first step when incorporating other supply chain partners. Partnership formation was a key element in all ten of the pilots and discussed to greater depth in the informational interviews and even great depth in the case studies. Obtaining a funding source as an enabling condition might seem obvious , however, acquiring funding through a series of grants, partnerships and endowments was perceived as both a necessary enabling condition and barrier for the majority of the pilots scaling past the trial stage (i.e., due to lack of consistent funding). The pilots that did not express funding source as a potential barrier were the pilots launched from within established seafood brands such as Bumble Bee Seafoods, Pacifical, and Raw Seafoods.

Robust traceability requires layers of electronic monitoring systems operating in concert to deliver the minimal functions that are needed for digitally monitored, recorded and verifiable data in the seafood sector. Ultimately, the innovation that is still being diffused in the seafood sector is robust, accurate, and real-time data recording through electronic monitoring systems. Blockchain, in this context, is one methodology that enables secure and immutable digital recording of the data collected by pre-existing digital monitoring systems. Computer vision models can aid in the detection of fishermen in a scene when they are close to the vessel's edge in order to flag the particular localization as “dangerous” or “not dangerous” in the scene for post-voyage auditing. In this research, I analyzed the drivers, enabling conditions, perceived barriers and steps taken to address those barriers in a set of ten potential adopters who are interested in the potential value add of blockchain technology. I applied the insights generated from the information interviews and grey literature review to the five stage diffusion process in order to understand what each stage requires of the actors in the social system that is the seafood supply chain. Further, a proof of concept system was used at-sea vessel imagery to vet the opportunity space for using computer vision for worker safety initiatives at sea. Given that fishery management through electronic monitoring is an effective tool to combat a wide spectrum of use cases, from mass overfishing [29] to fishermen safety at sea [47], the diffusion of resilient digital monitoring infrastructure is well-deserving of our efforts in the seafood sector.

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