UTS

Project Final Report

BeFAQT

Blockchain enabled Fish provenance And Quality Tracking

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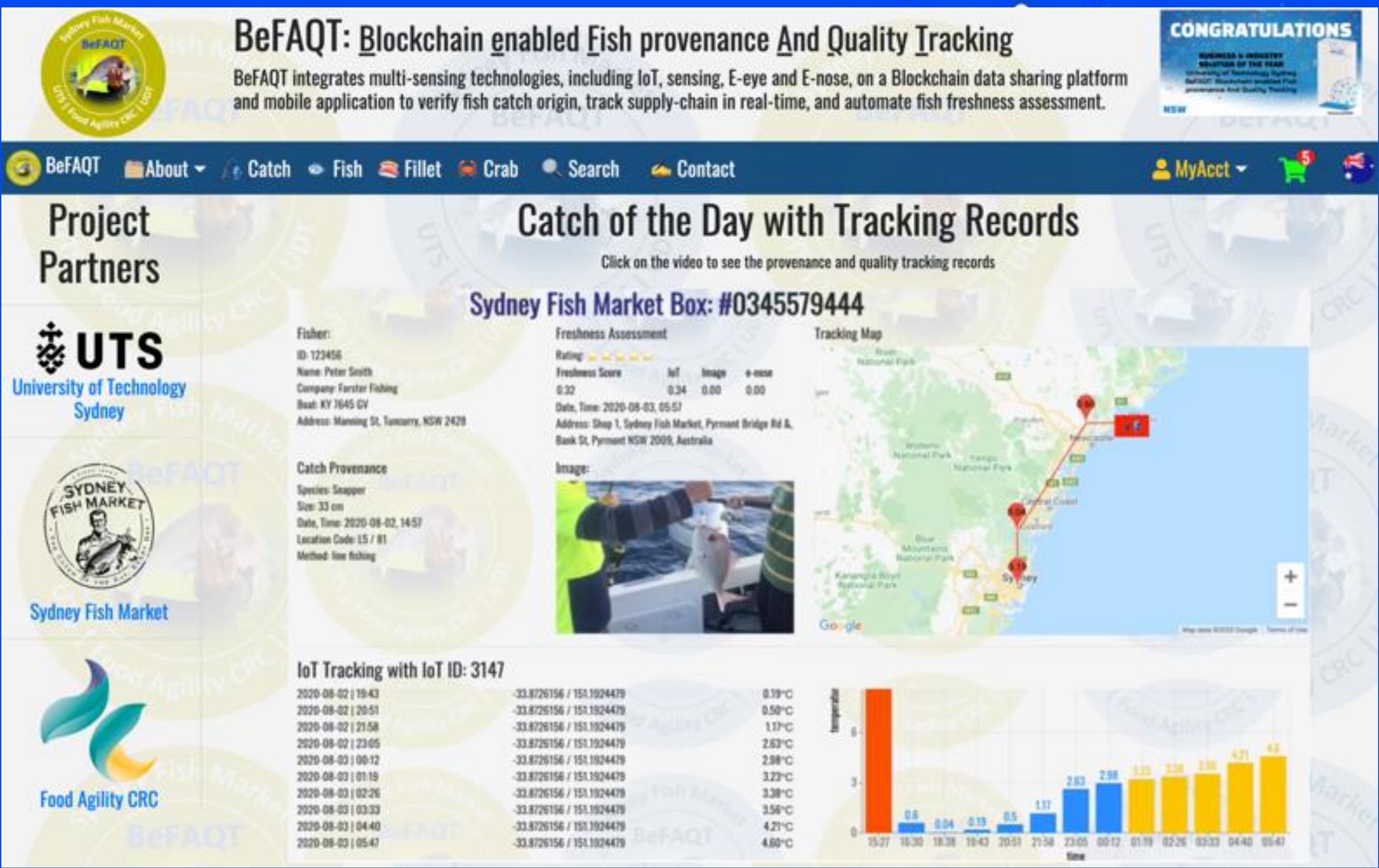

Contents

Summary

Seafood auctions start from 5:30am every weekday at Sydney Fish Market, where buyers inspect the produce before their bidding. Sydney Fish Market had been planning to develop an online version of its famous seafood auction. The challenge then was how to provide the same onsite inspection experience (see, feel, and smell) to the online buyers. In 2018, the Food Agility CRC organised two workshops attended by representatives from Sydney Fish Market, UTS research teams, Fisheries Research and Development Corporation (FRDC), Fishermen's Co-operatives, NSW Department of Primary Industries (DPI), Ultimo Digital Technologies, and WWF. The workshops identified a number of challenges, including the lack of fish origin and quality information within fish supply chains, as important constraints to innovation and growth in the seafood industry.

The UTS research team proposed to develop a Blockchain enabled Fish provenance And Quality Tracking (BeFAQT) system to overcome the fish supply chain challenges. In this project, the BeFAQT team has developed a wide range of technologies, including Internet of Things (IoT), e-eye, e-nose, blockchain enabled mobile App and online platform. The developed technologies have been trialled within the fishing industry. In particular, the IoT, Blockchain platform and App technologies have been trialled with fishermen to secure fish catch origin and supply chain tracking. The e-eye and e-nose technologies have been trialled for freshness assessments in Sydney Fish Market, where thousands of fish samples are collected and analysed. The BeFAQT system is being integrated in Sydney Fish Market's online trading platform to deliver blockchain secured provenance and quality tracking data to the buyers.

The BeFAQT system enables the online buyers to achieve better than onsite inspection experiences, in that they can not only have the see, feel and smell experience, but also have access to comprehensive information in seafood provenance, supply chain tracking, and quality assessment. With BeFAQT system, online buyers can have early access to catch list, including authenticated fish photo, species, and sizes, with trusted origin, visible condition tracking, and objective quality assessment. The developed BeFAQT technologies support Sydney Fish Market online trading platform to achieve simplified process, transparent and trusted supply chain, shorter time to market and wider market access.

BeFAQT won the NSW iAwards 2020 for Business & Industry Solution of the Year!

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1 Blockchain

The local fish supply chain of SFM is illustrated in Figure 1. The process starts from P1, i.e., fishing by domestic fishers near coasts. After fishing, the fishers pack the harvested fishes into boxes, which are rented from SFM, at local Co-Ops. Meanwhile, the fishers print paper labels, containing fishing date, fish species, sizes and others, and attach the paper labels on the boxes. The boxes of fishes are temporally chilled and stored in cool rooms at about 0 °C and then transported to SFM by local Co-Ops. When the fishes arrive at SFM, SFM can read the fishing information from the paper labels and then sell the fish, mainly in the form of Dutch auction. Before the auction, SFM and buyers need to assess the fish quality manually. After the auction, the buyers distribute the fish at SFM, fish shops and restaurants.

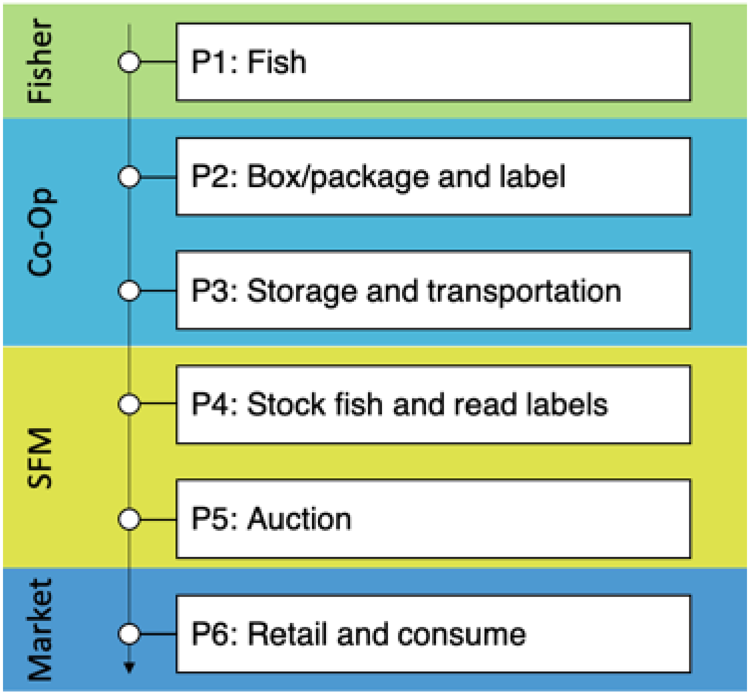


Figure 1 The supply chain of SFM.

1.1 Blockchain-based System Design

Being a distributed, incorruptible and tamper-resistant ledger database, Blockchain has the potential to address the critical security issues of IoT, particularly on data integrity and reliability. Blockchain allows software applications to send and record transactions/events in a trustworthy and distributed (peer-to-peer) manner. Blockchain is rapidly gaining popularity and used extensively for applications including smart contracts, distributed storage and digital assets. The potential applications of Blockchain in IoT include recording events (such as temperature, moisture or location changes) and creating tamper-resistant ledgers that are readable only to certain parties, e.g., specific participants in a supply chain.

With the Blockchain technologies, the security requirement of IoT can be fulfilled. The following prominent features of Blockchain can contribute to the integrity of IoT applications and so enhance the IoT security:

- *Decentralization:* The peer-to-peer network setting of Blockchains is inherently suited for IoT networks which are typically distributed. Blockchains can record transactions between multiple parties without central coordination. This can provide flexible network configurations and reduce the risks of single-point failures.
- *Integrity:* Blockchains are able to keep transactions permanently in a verifiable way. Specifically, the signatures of the senders in transactions can guarantee the integrity and non-repudiation of the transactions. The hash chain structure of Blockchains ensures that any recorded data cannot be

updated, even partly. The consensus protocols of Blockchains can guarantee valid and consistent records. The protocols can also tolerate failures and attacks. All these are critical to IoT applications, where IoT data can be generated and processed by heterogeneous devices or in heterogeneous network environments.

- *Anonymity:* Blockchains can use changeable public keys as users' identities to preserve anonymity and privacy. This is attractive to many IoT applications and services, especially those which need to keep confidential identities and privacy.

Interests in applying Blockchain to IoT networks have already emerged in academia and industry, with the goal of providing security. In this sense, cloud can provide distributed storage for IoT applications, while Blockchain can secure the integrity of the storage and prevent data tampering. Blockchain and cloud can be integrated as Blockchain-based Distributed Cloud.

The proposed Blockchain-enabled fish provenance and quality tracking system adopts Blockchain as a trust centre, integrates the latest IoT tracking, E-eye and E-nose technologies, and provides user-friendly applications for various users, as shown in Figure 2.

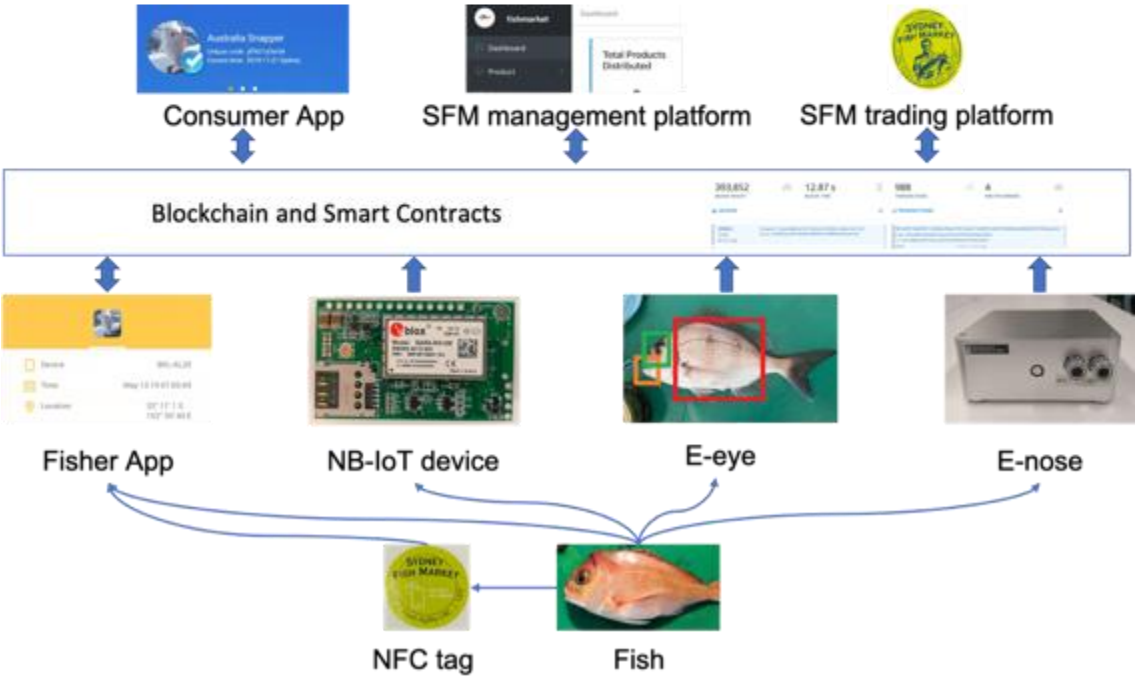


Figure 2 System Overview.

Each SFM fish box is identified by a unique ID, denoted by the *fish ID*, which is stored in a Near Field Communication (NFC) tag on the box. The NFC tag enables the fish box to interact with other modules and participants' mobile phones easily. We design a Fisher App and NB-IoT device for the fish provenance proof where the Fisher App can take fishing photos, and the NB-IoT device is mounted on the fish box to track location and temperature. We also introduce the image processing and E-nose to assess the fish quality from vision and odour perspectives, respectively. The Blockchain runs as a trusted data platform enabling real-time online monitoring and tracking of fish products. Consumers can track and verify their purchased products in terms of provenance, trace, and quality indices. The system can also be integrated into the trading platform of SFM by providing Blockchain-certified provenance proof and quality tracking information through Application Programming Interfaces (APIs).

1.2 Blockchain Platform and Consensus Protocol

Based on access controls of the Blockchain networks, the state-of- the-art Blockchains can be categorized into public Blockchain, private Blockchain, and hybrid Blockchain which mixes of the former two.

- Public Blockchain: The dominant class of Blockchain is public Blockchain in which, with no access control, any uncertified, untrustworthy node can read and record transactions, and take part in mining blocks and contributing to Blockchain. Designed for open access public distributed networks, public Blockchains can provide strong scalability. However, preserving the consistent records of public Blockchain becomes increasingly difficult, as the network scales up, and would compromise the block generation rate of public Blockchain consequently. This is due to the fact that, without access control, public networks do not have strict control policy on the identification and certification of any participants, and therefore the implemented consensus protocols have to scarify the block generation rate for security. Current public Blockchain projects, including Bitcoin and Ethereum, also demonstrate the openness and capacity-limited characteristics. Public Blockchain is suitable for the IoT applications with open access or flexible peers at a large scale, such as VANET and supply chain.
- Private Blockchain: Another popular class of Blockchain is private Blockchain which resides in closed proprietary networks with stringent access control and read/write permission, as well as participant identification and certification. Private Blockchains can meet the privacy requirement and has been increasingly drawing attention from financial institutions. The proprietary networks, on which private Blockchains operate, can be optimized for high speed and low latency. For example, a high speed of up to tens of thousands of transactions per second can be achieved in private Blockchains. Private Blockchain adopts BFT protocols, i.e., PBFT and its variability, as consensus protocols, which provide higher capacity with restricted access control. The access control provided by private Blockchain further protects IoT applications from external adversaries. In general, private Blockchain is suitable for IoT applications with small scale of miners, because of the high communication complexity and overhead of BFT protocols. When the network size goes beyond twenty, the capacity of private Blockchain dramatically slows down. Apart from various BFT consensus protocols, private Blockchain can use other efficient consensus protocols, e.g., Paxos and Raft, in response to specific types of failures, e.g., crash failures and fail-stop failures.
- Hybrid Blockchain: Another class of Blockchain is hybrid Blockchain which was proposed to leverage the advantages of public and private Blockchains, to be more specific, the block generate rate of private Blockchain and the scalability of public Blockchain.

1.2.1 Consortium Blockchain and Consensus Protocol

In the system, Blockchain is designed to be maintained by large organisations in the fish trading process, e.g., SFM and big Co-ops, and ensure data integrity to all participants, e.g., fishers, Co-ops, SFM and consumers. We design a consortium Blockchain for the system rather than a public Blockchain because of the outstanding features of consortium Blockchains, e.g., high throughput, low computation and storage cost. The consortium Blockchain meets the trust requirement, where SFM and few Co-Ops act as Blockchain miners to validate transactions containing fish provenance and quality tracking data and preserve the transactions in blocks.

The miners run a widely used consensus algorithm in consortium Blockchains, i.e., Practical Byzantine Fault Tolerance (PBFT) algorithm. Byzantine Fault Tolerance (BFT) is typically used in private/consortium Blockchain to formulate consensus protocols and guarantees consistency by exploiting the solutions to the Byzantine Generals' Problems — agreement problems. Particularly, the PBFT algorithm [18] has been extensively used to eliminate the Byzantine failures. In 1999, Castro and Liskov proposed the first Byzantine- fault-tolerant, state machine replication algorithm, named ‘‘practical Byzantine Fault Tolerance (PBFT)’’. As a leader-based BFT algorithm, PBFT has one primary and $(n-1)$ backups in an n- node network, where the backups can be corrupted. The primary is responsible for receiving the requests from clients and initializing the algorithm. Inspired by View stamped Replication, PBFT consists of four stages: (a) a client sends a request to invoke a service operation to the primary; (b) the primary multicasts the operation to the backups; in specific, the primary (replica 0) assigns the sequence number to the m-th request from the client and multicasts a PRE-PREPARE message with the assignment; (c) replicas execute the request and reply to the client; If a backup agrees on the assignment, i.e., correct and validated parameters, it multicasts a PREPARE message. When a backup receives messages that agree on the assignment from a quorum, i.e., $2f$ validated and consistent PREPARE messages from different backups, it multicasts a COMMIT message. A backup executes the request m and sends a reply to the client after receiving $2f$ validated and consistent COMMIT messages; and (d) the client waits for $(f+1)$ replies from different replicas with the same result which is the result of the operation tolerant to up to f failures.

The PBFT algorithm is resilient. It has been proved that the PBFT algorithm can ensure n peers within a synchronous and reliable network to reach consensus, as long as there are no more than n−1 betrayed 3 peers. Specifically, the algorithm only requires $n \geq 3f + 1$ replicas to tolerate up to f faulty replicas and guarantee the consistent, fault-free output to the client. This is because ($3f + 1$) PREPARE messages at any backup node, including its own, are sufficient at the second stage for a credible, uncorrupted backup to generate a genuine COMMIT message. The third and fourth stages can both guarantee the received consistent replies to outnumber the up to f faulty replies at any backup and the client. The PBFT algorithm is efficient and is able to process thousands of requests per second with processing latency in sub-milliseconds. However, PBFT necessitates all participating nodes to be adequately identified, certificated and authorized. For these reasons, the PBFT algorithm is suitable for private Blockchain in a relatively small and controllable scale.

In this project, the consensus process can be divided into three stages, i.e., *pre-prepare*, *prepare* and *commit*, as shown in Figure 3. The block proposer, e.g., Co- Op 1 in Figure 3, is appointed by the round-robin scheme. In order to improve the throughput, we follow the principal steps of PBFT but reduce the data transmission during the consensus. Specifically, the whole block is only transmitted at the *pre-prepare* stage. The hash value of the block, rather than the whole block, and signatures are transmitted at rest two stages to reduce the communication cost and then improve the throughput.

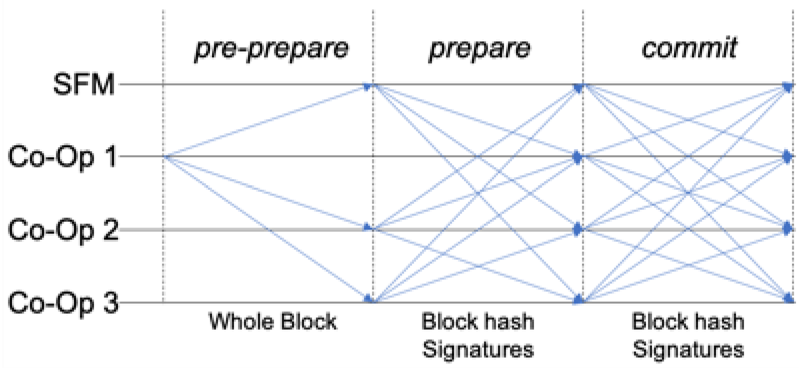


Figure 3 The consensus process among miners.

1.3 Smart Contract-enhanced Fish Tracking

A smart contract is a piece of cryptographically secured execution of code that runs on the basis of Blockchain. Without any assistance of third parties, the smart contract self-executes the corresponding contractual clause once the defined condition is triggered. In addition, it also provides real-time auditing, since all actions are recorded and verified as transactions in a decentralized Blockchain ledger. These transactions are trackable and undeniable, hence enhancing the machine-execution security. Smart contract translates various assets, such as IoT devices and digital assets, into virtual identities in Blockchain, and enables them to interact with other assets. Smart contract is appealing to replace normal contracts as an efficient and secure method. The code of smart contract is stored in Blockchain and identified by a unique address. A smart contract can be called in two ways: one is by validated transactions with a smart contract address in the receiver field; the other way is the internal execution of code. Therefore, all execution records can be traced using the Blockchain ledger. The smart contract is executed independently and automatically on every node in the Blockchain network. Several Blockchain projects, including Ethereum and Bitcoin, have implemented smart contract. As IoT expects sensors in unmanned areas running and acting automatically with defined rules in decentralized manner, the smart contract has the potential to improve the efficiency and security of IoT applications. IoT devices can carry out autonomous transactions through smart contracts.

We design a smart contract to collect the fish provenance and quality tracking data and provide the data to users. The workflow is shown in Figure 4. The smart contract includes the following functions,

- Fish Info Registration Function: This function collects fish provenance data (i.e., fish ID, fishing time, fisher information, Co-Op information, location of the fishing point, fishing photo hash value and photo

URL) from Fish Apps, tracking data (i.e., fish ID, location, time, and temperature) from IoT devices, and fish quality data (i.e., fish ID, time, fish species, size, and quality measurement) from image processing and E-nose modules. This function then organises all the data according to the fish ID given in the transactions calling this function.

- Fish Info Retrieval Function: This function searches the stored fish provenance and quality tracking data according to the fish ID given in the transactions calling this function and then returns a list of the fish data.

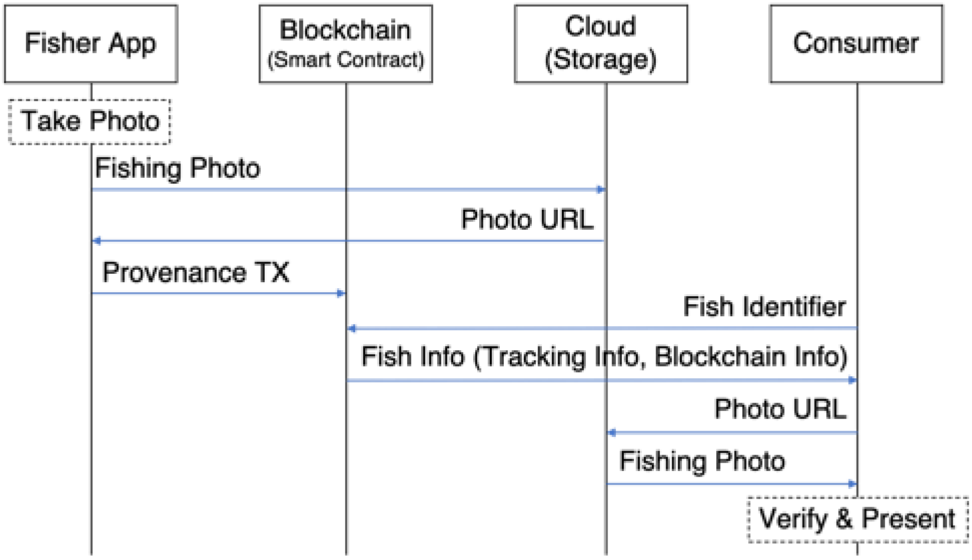


Figure 4 The workflow of the smart contract-enhanced fish tracking.

The smart contract would be confirmed by SFM and all Co- Ops, and then deployed on the Blockchain by any participant, e.g., SFM. After being deployed, the smart contract can be triggered by smart contract transactions issued by the registered modules, i.e., Fisher Apps, IoT devices(servers), E-eye and E-nose modules. Note that these modules only sign transactions and send the transactions to the Blockchain through Remote Procedure Call (RPC). The modules do not run the consensus protocol nor store Blockchain data, which significantly reduce the computation, storage and communication cost.

2 Mobile App

We design mobile app for both fishers and consumers to provide easy-access to Blockchain-certified fish quality tracking services. The app has a built-in Blockchain module to create and sign Blockchain transactions and therefore can call the smart contracts in the BeFAQT Blockchain. The mobile app fully utilizes mobile sensors, such as mobile cameras and NFC sensors for user-friendly functions.

The mobile app can be divided into Fisher App and consumer app. The Fisher App is designed for fishers where fishers can create fish catch provenance and update the quality tracking information. The consumer app is designed for consumers where consumers can retrieve Blockchain-certified fish quality tracking information.

2.1 Fisher App

2.1.1 Function Design

We design a Blockchain-based Fisher App to realise fish provenance. The Fisher App can be installed on fishers' mobile phones and enables the fishers to take Blockchain-certified photos of the catch, then the fish photos, together with time and location, are locked with certificates (hash values) and uploaded to the Blockchain. We also engage with NSW Department of Primary Industries (DPI) to integrate our development with the NSW DPI App (an information App for fishers). Key modules of the Fisher App are shown in Figure 5. The left-hand side lists key modules supporting the Fisher App, while the right-hand side shows the functions that users would use.

Figure 5 Modules of the Fisher App.

1. Interact with Blockchain

The workflow of the Fisher App is shown in Figure 4. Every Fisher App instance has a unique Blockchain private key to sign Blockchain transactions with fish provenance information. The Fisher App can take fishing photos while recording the time and location, and then calculate the collision-resistant hash value of the photos as a proof of origin. To save the storage cost of Blockchain, the Fisher App uploads the photos to the cloud storage and obtains the Uniform Resource Locator (URL) from the cloud storage. After that, the Fisher App will call the fish provenance smart contract on the Blockchain to register the photos, where the fish provenance data are provided as parameters.

2. Fisher management

The Fisher App can only be operated by registered and authorized fishers to ensure the data trustworthy. The Fisher App can use BeFAQT server for fisher verification and would present the profile of the fisher. Meanwhile, every fisher has a unique Blockchain private key to sign the transactions containing fish quality tracking data.

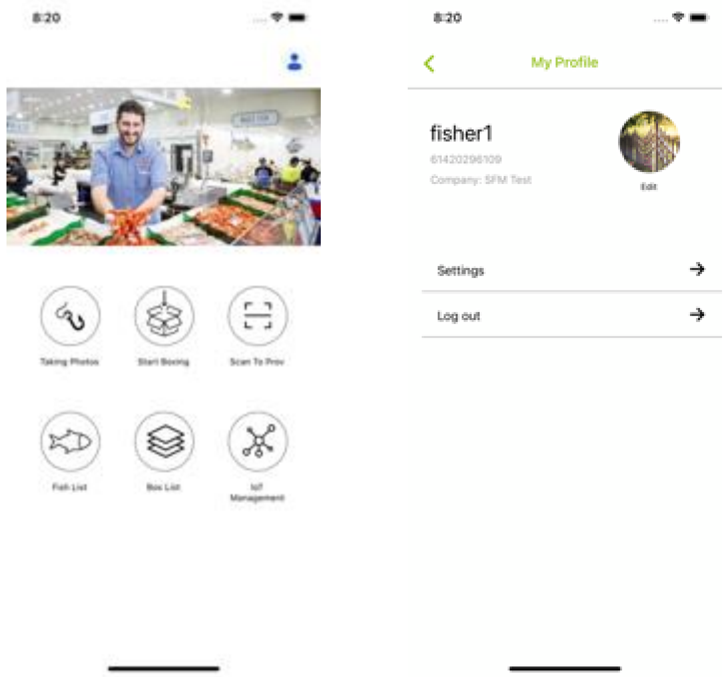


Figure 6 Main page and the profile page of the Fisher App.

3. Task management

This module allows fishers to view historical tasks, e.g., the catch provenance and E-eye tasks. This module also enables fishers to link tasks with specific boxes.

4. Integration with E-eye

The Fisher App is designed to support E-eye module in the BeFAQT for species recognition, sizing and freshness measurement. We have identified two typical cases: 1. fishers use the App to take photos for species recognition at Co-ops; 2. SFM staffs use the APP to take photos for freshness identification at SFM before the auction. The workflow is shown in Figure 7. The image processing will be deployed on a server to process the request from the App and BeFAQT server. In this way, fishers and workers can enjoy the image processing algorithm on their phones. To be specific, the Fisher App can take fish photos at Co-Ops or at SFM. The photos quality, such as photo resolution and light condition, follow the requirement of E-eye. The photos are uploaded to cloud storage rather than the Blockchain. This is because the Blockchain only support limited storage and cannot support massive photo storage. The app then notifies the BeFAQT server that meta data of the photos, e.g., URLs to the cloud storage. The BeFAQT server then call the E-eye server to start the image processing tasks, i.e., species recognition, sizing and freshness measurement. The E-eye server can then retrieve the photos from the cloud storage and analyze the photos. The result will be sent back to the app via the BeFAQT server rather than directly from the E-eye server. In this way, the E-eye service is transparent to the App.

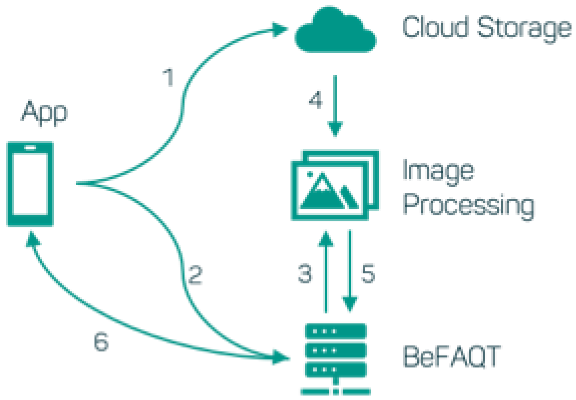


Figure 7 The integration of the Fisher App and E-eye

5. Fish provenance and quality tracking

Fishers can use the Fisher App to take fish photos for fish provenance and quality tracking. Typically, fishers take fish photos while the fish is caught for fish provenance proof and when the fish is transported via Co-Ops. To be specific, the Fisher App can take fish photos that will be uploaded to cloud storage. When the photos are taken, the location and time are automatically acquired by the Fisher App to avoid human bias. The app then registers the photos meta data, e.g., location, time, photo URL, photo hash, and fisher info, to the Blockchain.

2.2 Consumer App

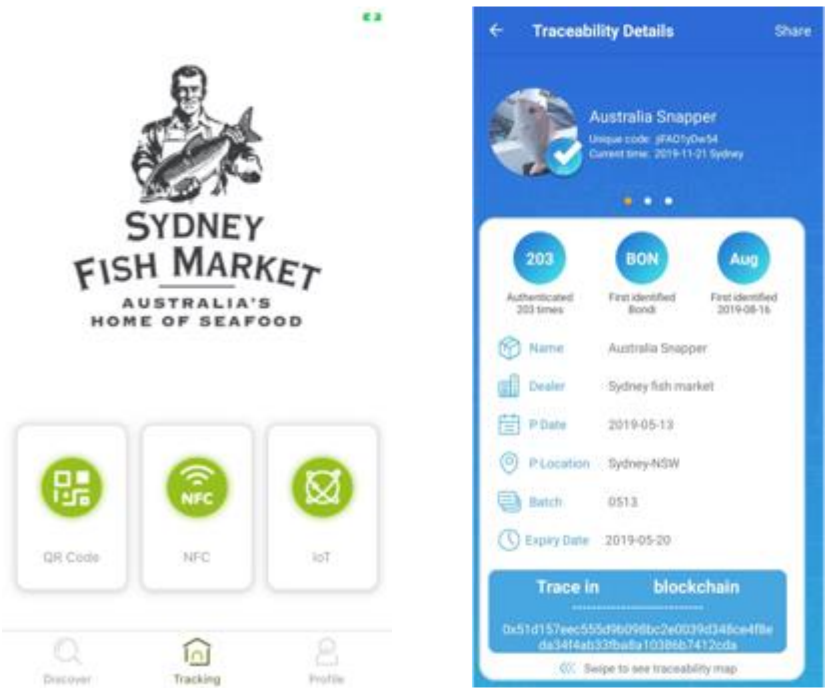


Figure 8 Main page and the quality tracking result of the consumer App

The consumer app is designed to provide Blockchain-certified catch provenance and quality tracking data to consumers. Consumer can use the consumer app to tap the smart NFC tags, as shown in Figure 9, to get the Blockchain-certified fish provenance and quality tracking data. Near-Field-Communication (NFC) is a set of communication protocols for communication between two electronic devices over a distance of 4 cm or less. NFC offers a low-speed connection with simple setup that can be used to bootstrap more-capable wireless connections. NFC devices can act as electronic identity documents and keycards. They are used in contactless payment systems and allow mobile payment replacing or supplementing systems such as credit cards and electronic ticket smart cards. Every box of fish is identified by unique number which is stored in the NFC tag.

At the SFM or other places where fish quality are assessed, consumers can use the consumer app to tap the NFC tag attached on the fish box to read the unique box number from the NFC tag. The consumer then sends the box number to the BeFAQT server and also the BeFAQT Blockchain. The server and Blockchain can search related provenance and quality tracking data with the box number and then return the data to the consumer app. After received the provenance and quality tracking data, the consumer app will verify the data from the Blockchain and then present the data to users.

Figure 9 The smart tag with built-in NFC chip.

3 IoT

[Ying He]

The quality of fish is affected by various conditions of the supply chain. Traditionally the supply chain was managed by manual paper passing. One problem with this approach is that it does not allow real-time monitoring of the environmental conditions such as the temperature and humidity. The operators may not even be aware of the extreme conditions that the food is being subject to. Another problem is that the manual paper passing and even the recent advancements of RFID cannot be trusted as they can be forged by dishonest supply chain operators.

The Internet of Things (IoT) enables real-time tracking of assets and the environmental conditions in the supply chain. In Australia, both Telstra and Vodafone have provided Cat-M connectivity and completed their preliminary trials to provide connectivity to IoT devices through the Narrow Band IoT (NB-IoT) technology. However, currently there are no commercial products using NB-IoT technology for food quality monitoring.

We have designed the low-power IoT device and developed firmware running on the device to sense the environmental temperature, obtain GPS coordinates, time stamp, and transmit the data to the cloud server. Blockchain platform will fetch the data from the cloud server, re-order the data according to the packet index and upload the data to Blockchain.

Figure 3.1.1 shows how IoT device integrates with cloud server and the overall BeFAQT system.

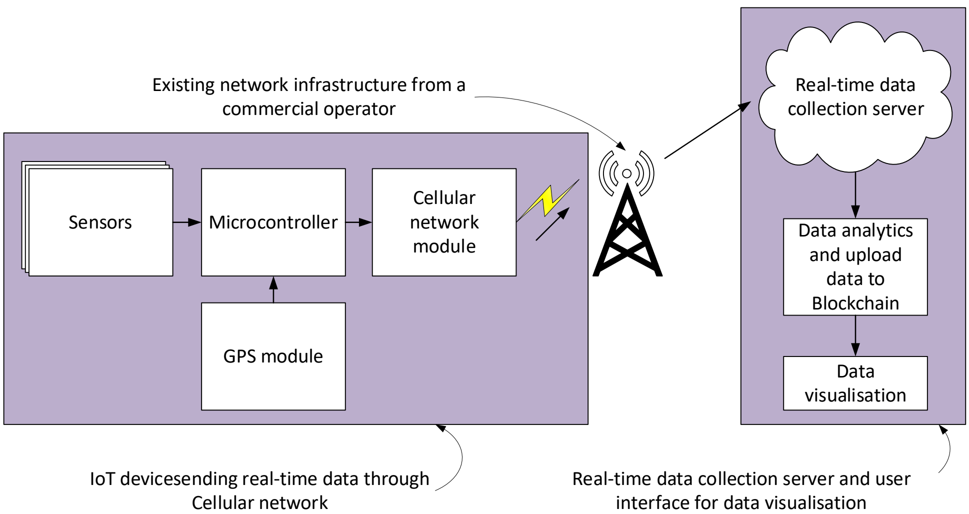


Figure 3.1.1 IoT system architecture

3.1 Hardware Design

We chose ARM Cortex M0 microcontroller, ublox R410M cellular network module, GPS module and temperature sensor to construct the basic architecture of the hardware.

Main firmware is uploaded and running on the microcontroller.

- Connection between the microcontroller and the cellular network module is used to read/write from and to the serial buffer on each end. Microcontroller will send AT commands to the cellular network module and read the response back via the connection.
- Connection between the microcontroller and the GPS module is used to write the GPS settings and read the received data via GPS, including coordinates and timestamp.
- Connection between the microcontroller and the sensors is via I2C, digital or analog port.

- Connection between the microcontroller and the micro USB port is used for programming and debug purposes. When the board is in programming and debug mode, we use the USB port to connect to a PC to upload firmware to the microcontroller and view the responses from the microcontroller, including the responses from the cellular network module.

The cellular network module is connected to the RF and sim slot. We designed external antenna ports for LTE antenna and GPS antenna to reduce the board size and provide an option for extending the antenna placement, for example, when the device needs to be mounted inside of a fridge/truck, we have the option to place the antenna at the outside of the fridge/truck to obtain a clear reception.

Power unit takes input from micro USB (same port for programming) or battery connected to the interface. When both USB and battery are connected, battery will get charged and the board will get power supply from the USB.

We designed two environmental sensors. One BME690 sensor that is designed to be onboard. It can obtain temperature, humidity, pressure and gas. Another DS18B20 temperature sensor with waterproof probe which is an external sensor. The external sensor is designed to be placed inside of the fish box to obtain accurate temperature of storing the fishes.

Onboard LEDs are programmed to show running and charging modes.

The hardware design went through two phases and we had 2 versions of the IoT board. The basic model is the same between 2 versions as described above.

Table 3.2.1 Main difference between IoT device v1.0 and v2.0

Item	Change	Reason
Sim slot	Micro sim in v1.0 and nano sim in v2.0 Fixed wiring errors in the design in v1.0	Reduce sim slot size
Battery connection	JST connector 2.5mm in v1.0 and 1.25mm in v2.0	Reduce connector size and increase stability

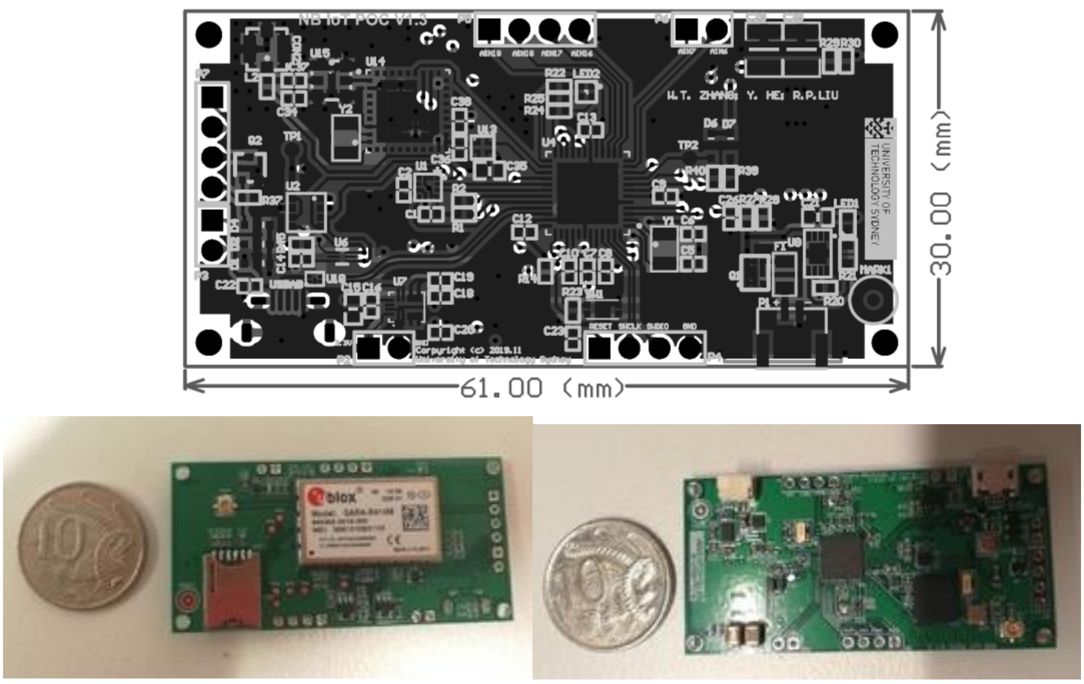


Figure 3.2.1 IoT device v2.0 hardware design layout and PCB sample

3.2 Firmware Design

The application of our design is to track fish from catch to market along the supply chain. The temperature range is approximately -2 to 40 °C, which includes when the fish box is filled with ice or empty box in room/outdoor temperature. Possible scenarios are:

Table 3.3.1 IoT application scenario

Scenario	GPS availability	Cellular network connectivity	Mobility
Indoor cool room/fridge	No GPS	Limited	No
Indoor	No GPS	Normal	No
Outdoor shipping	GPS	Normal	Low speed
Outdoor shipping	GPS	Slow/interrupted due to mobility	High speed
Outdoor near shore fishing	GPS	Normal	No
Outdoor remote off-shore fishing	GPS	Limited due to distance to the basestation onshore	

According to individual component power consumption, GPS module consumes approximately 40% of the total power when all components are running, running after is the cellular network and RF components. To meet the requirements in different scenario and avoid unnecessary activities in GPS module and cellular network, we designed the firmware with active window and sleeping window.

In each active window, the firmware attempt to connect to the cellular network, obtain GPS information, read the temperature sensor and transmit the data to the cloud server. If all steps are successful, the firmware will enter the sleep window and turn off cellular module, RF and/or GPS module. A watch-dog is configured with an interval. When the interval is time-out, firmware will wake the device up and enter the next active window.

In different scenarios, the connectivity and availability of the cellular network and GPS reception may vary. This will lead to unsuccessful in attempts in the active window. Delay windows with configured short intervals and maximum number of attempts are configured to re-attempt. When GPS reception is available, timestamp will be parsed from the received GPS data. When GPS reception is not available, timestamp will be parsed from cellular network. When cellular network is not available, but GPS reception is available, the GPS data and temperature value will be buffered, until next active window when cellular network is available, all buffered data will be transmitted.

Each packet, including new and buffered data, will be labelled with an accumulative index. This index will be used by the cloud server to re-order the received packet. Buffered data will be transmitted with a tag. The index will reset when the microcontroller resets.

Firmware is designed and implemented with standard C. The flowchart of normal working loop is as Figure 3.3.1. Firmware is designed to be able to run automatically without any manual configuration. Firmware can loop, search the network, fetch GPS and sensing data and send the data out. We have also programmed the on-board LED to flash different patterns for different stage of the working loop for monitoring purposes. The firmware can run in either auto or manual modes:

SERIAL_FORWARDER_MODE_ON=0: device is in auto-run mode.

SERIAL_FORWARDER_MODE_ON=1: device is in serial forwarder mode and it needs to be manually configured via serial interface via PC. This is a mode for debug purpose.

DUMMY_GPS_MODE_ON=1: when device is in auto-run mode, if the device is indoor, it needs to be configured with a dummy GPS location and the dummy GPS mode on. When the device is outdoor, it needs to be configured with the dummy GPS mode off. This is a mode that can be used for debug purpose. DEBUG_STREAM_ON=1: device can be in any of the above 3 modes, microcontroller will print messages to the serial interface to PC and show on Arduino IDE serial monitor.

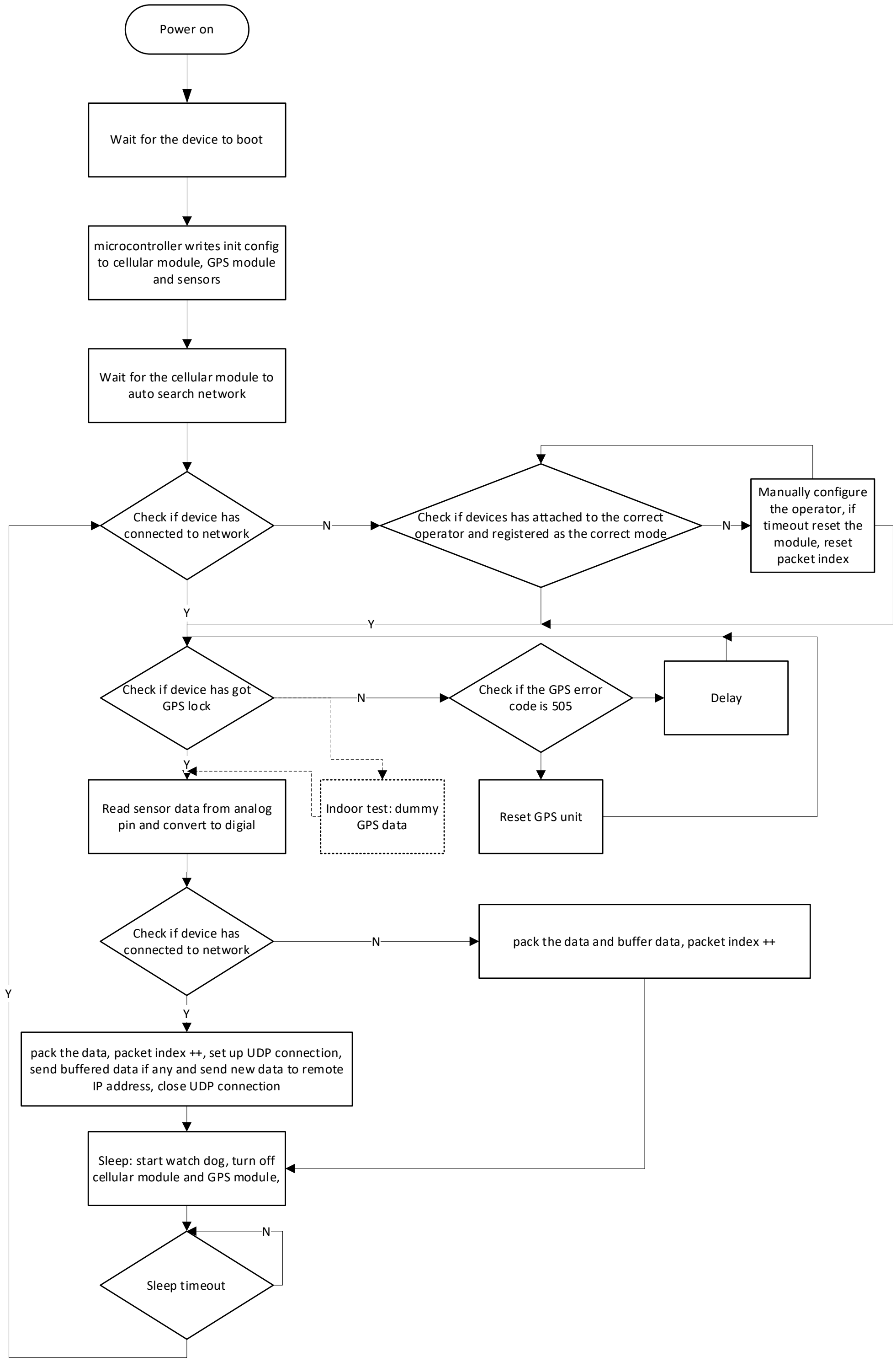


Figure 3.3.1 IoT firmware flow chart

3.3 Enclosure Design

We used off-the-shelf water-proof enclosure to install v1.0 IoT board. The external temperature sensor goes through the enclosure to the inside of the fish box via the cable gland.

Figure 3.4.1 Installation with off-the-shelf enclosure with cable gland for the external temperature sensor

The off-the-shelf enclosure with external sensor is able to obtain accurate temperature inside of the fish box. We improved this design to avoid physical cable running inside of the fish box and increase the flexibility of enclosure installation and removal. We designed a 3D-printed water-proof enclosure to install v2.0 IoT board. The enclosure is designed to connect the temperature sensor to the metal foil tape on the screw hole. When we install the enclosure to the fish box, the temperature will be passed via the metal screw, to the metal foil tape and reach the sensor. The exterior dimensions are designed to fit the enclosure on the side of the fix box to avoid blocking the paper label slot and enable fish box stacking storage. The interior dimensions are designed to fit the IoT board v2.0, antennas, external sensor and battery.

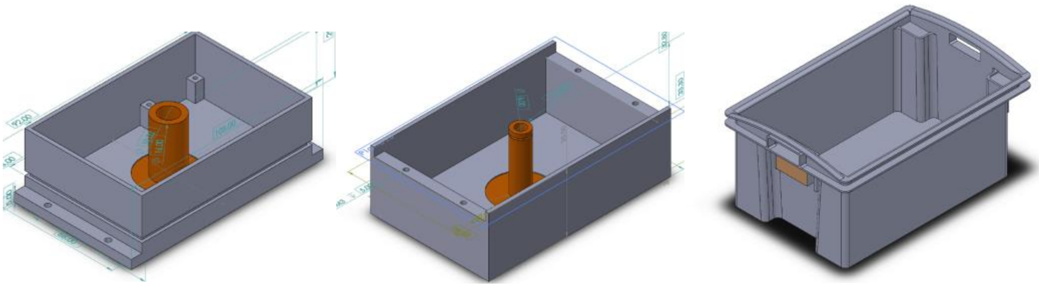


Figure 3.4.2 IoT device enclosure design model

Figure 3.4.3 IoT device enclosure 3D-printed sample and installation on the fish box

4 E-eye

[Jian Zhang]

The E-eye technology is to automatically achieve fish freshness identification, fish size measurement, and fish species classification through a mobile phone camera. For each of these three E-eye tasks, a constant light condition system called lighting-box is designed to enable high-quality dataset collection, and an AI model design. Moreover, a GPU-optimized image processing API system is developed and deployed onto the cloud, and integrated with the blockchain system and Fisher APP.

4.1 Overall Solution Structure

The three E-eye tasks are implemented based on image processing API system, which is optimised on GPU and deployed on the cloud. The image processing API system has been integrated into both the blockchain system and Fisher APP (see Figure 4.1). The fisher APP is responsible for capturing fish images and sending them to the blockchain system to request results. The blockchain system organises the requests and then sends captured images to the image processing API system to get the images results for the three E-eye tasks, including freshness, size and species.

Based on the system structure, these three E-eye tasks are split into two function channels based on the use scenario. As shown in Figure 4.1, the freshness assessment function placed in one function channel with a portable lighting box. This function is mainly applied in Sydney Fish Market after the fish auction day (see part (a) in Figure 4.1.) while the merged size measurement and species classification functions placed in other function channels with a standard blue box from Sydney Fish Market. This function focuses on the scenario of a fish caught to at the fish boat (see part (b) in Figure 4.1).

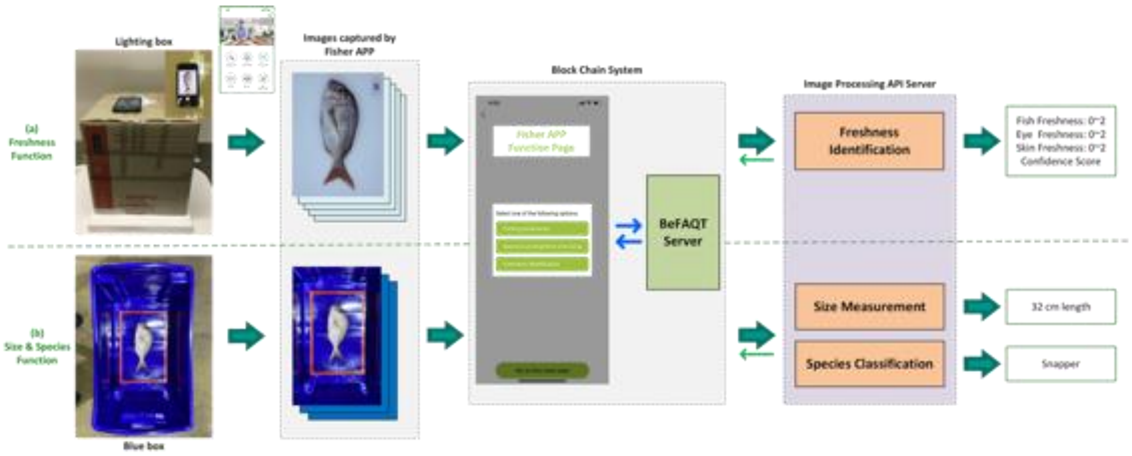


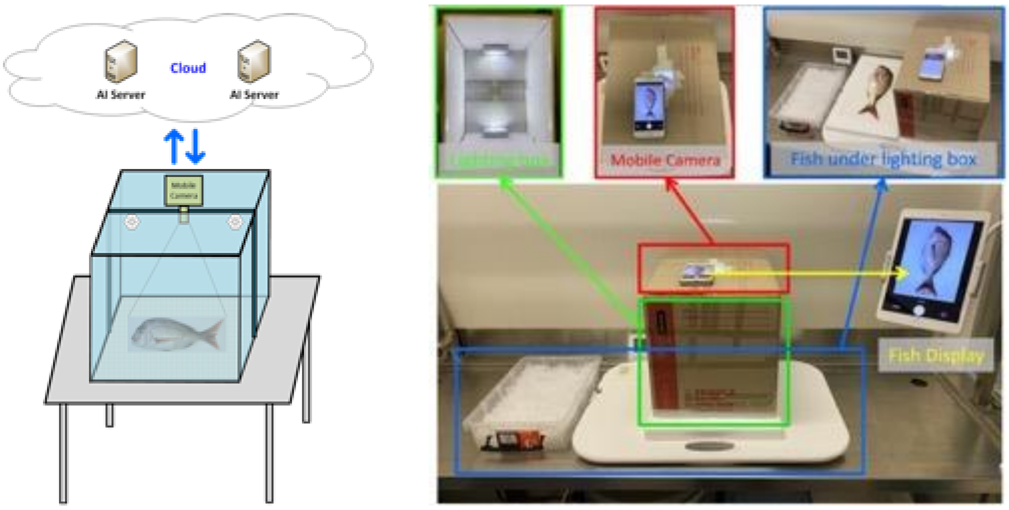
Figure 4.1 Overall structure of E-eye solution

4.2 Fish Freshness Identification

The technical solution of fish freshness assessment includes three key components: hardware system, data collection, and algorithm design. Pegrus Auratus Snapper is selected as the target species, as it is the most popular species in Australian fish market.

4.2.1 Hardware Design

The hardware system consists of a white tray, lighting box, and mobile (see Figure 4.2). The white tray is used for placing fish in its middle region and providing white-colour background. The lighting box covers the fish, providing a stable lighting condition for image capturing. The mobile (e.g. iPhone 11 pro max) is placed on the top of the lighting box and used for capturing fish images via its rear camera. Given the flat surface of the lighting box, the camera lens is positioned to be almost parallel to the surface of the fish.



(a) (b)

Figure 4.2 Hardware design for fish freshness identification

The lighting box is the most important hardware for fish freshness assessment, as it can provide a stable lighting condition to ensure the effectiveness of image processing. This can overcome the complex lighting conditions around different areas of Sydney Fish Market. See Figure 4.3, the lighting box prototype is designed with a thick mailbox, and two cool-colour LED lights. The inner surfaces are all covered with white papers. The two LED lights are placed at the top of the inner sidewalls to avoid heavy light reflection. As shown in Figure 4.3, parts (a) and (b) show the outside of the lighting box when the mobile camera is placed and turned on, parts (c) and (d) show the inside of the lighting box when LED lights are on and off.

(a) (b) (c) (d)

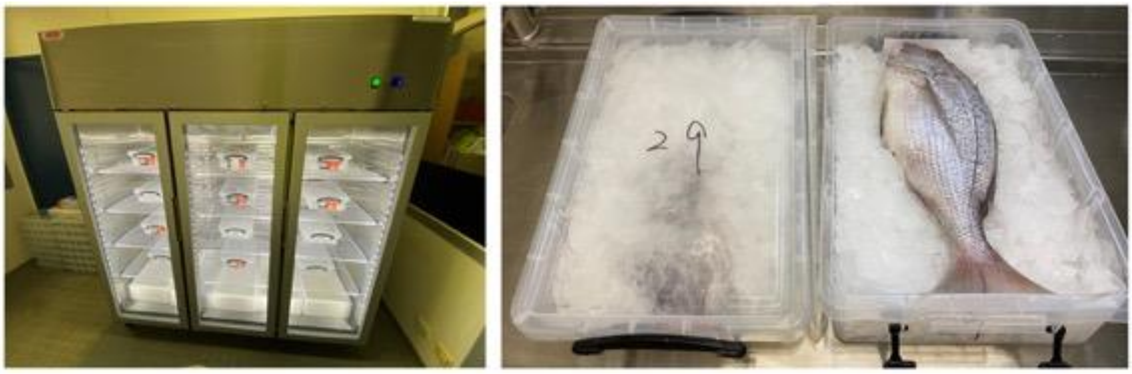
Figure 4.3 Design of lighting box

4.2.2 Dataset Collection

A high-quality freshness dataset is a premise for achieving high accuracy. The dataset collection involves three aspects: fish storage, fish freshness annotation and fish image collection. This dataset is used for model training and testing.

4.2.2.1 Fish storage

As shown in Figure 4.4, All fish boxes must be placed in a laboratory fridge within 0-4 temperature degrees (see Figure 4.4 (a)). Every fish is stored in a plastic container (see Figure 4.4.(b)) and covered with ice at both sides (see Figure 4.4 (b)), since the ice keeps the temperature at zero degree and prevent fish from getting dry.



(a) Laboratory fridge (b) Fish box

Figure 4.4 Fish storage

4.2.2.2 Freshness profile definition

The definition of freshness profile for Pegrus Auratus Snapper is designed based on the 'Seafood Quality Index APP', which is an official quality assessment from Sydney Fish Market. For E-eye function, only appearance-based freshness indices are extracted from the 'Seafood Quality Index APP'. See Table 4.1, freshness indices to three fish parts (i.e. skin, eye, gill) are extracted. The skin part has three freshness indices including pinkish colour, bluish spots and scales, which are used to decide the overall freshness of the skin part. The eye part has two freshness indices, including form and pupils, which are used to determine the overall freshness of this part. The gill has one freshness index – colour. Corresponding to each index, there are three freshness ranking levels, namely 0, 1, 2. Level 0 is the most freshness score, level 1 is the middle freshness score, and level 2 is the most non-freshness score. Examples of three levels are illustrated in Figure 4.5. The E-eye technology has adopted these freshness indices/levels to form the advanced freshness assessment system for Sydney Fish Market.

Table 4.1 Appearance-based Freshness Indices and Freshness Levels for Pegrus Auratus Snapper

Fish part	Freshness indices	Levels
Skin	Pinkish Colour	0-Bright red; 1-Pale; 2-Dull;
	Bluish Spots	0-Bright blue; 1-Pale; 2-Dull;
	Scales	0-Shiny and firmly attached; 1-Slightly dull and less firm; 2-Dull and loosening;
Eye	Form	0-Convex; 1-Flat, slightly sunken; 2-Sunken;
	Pupils	0-Clear and black; 1-Dark grey; 2-Matt/dull, grey;
Gill	Colour	0-Bright, characteristic red; 1-Slightly discoloured, brown/red; 2-Discolored, dark brown/green;

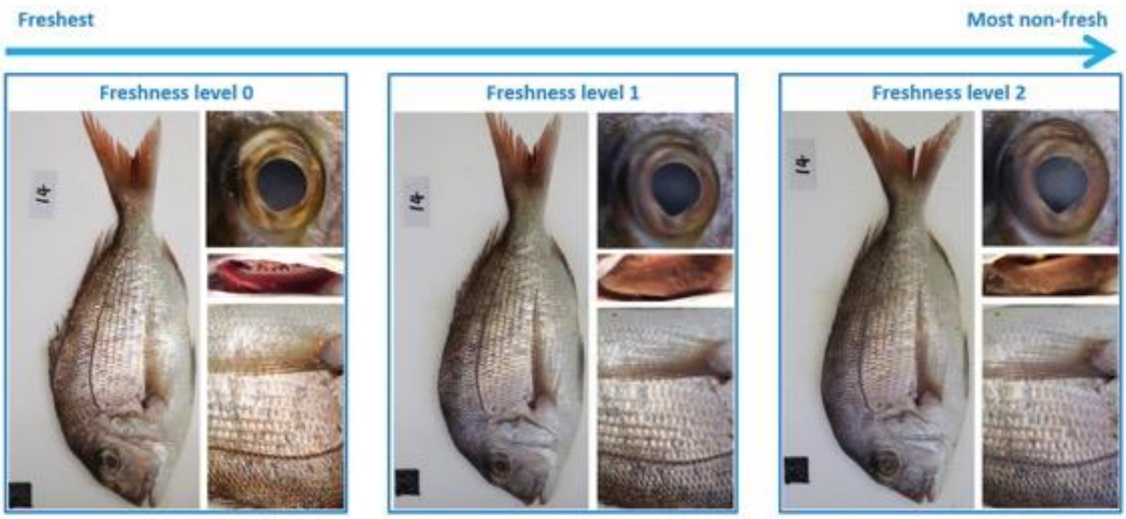


Figure 4.5 Examples of three freshness levels

4.2.2.3 Freshness annotation

Based on Table 4.1, the Sydney Fish Market QA team conducted the whole manual annotation tasks using the freshness annotation form, as shown in Figure. 4.6. The form is designed to cover all the aspects of Table 4.1 and with three extended overall scores. On the day of manual annotation, every collected fish is added an ID number and annotated with scores (0,1 and 2) for nine freshness indices as follows:

1. Skin freshness: pinkish colour, bluish spots, scales and overall score (4 indices and scores).
2. Eye freshness: form, pupils and overall score (3 indices and scores).
3. Gill freshness: colour (1 index and score).
4. The overall freshness score (1 index and score).

For image processing, we rename the freshness index and its score as fish annotation feature and its feature value. Therefore, we have nine fish annotation features and their feature values for Skin, Eye, Gill and Overall. The overall freshness score for each part (i.e. Skin, Eye and Gill) and the whole fish is manually annotated by the QA team but referred to the other annotation features. To have a complete data recording, both the date of annotation date and days of storage are recorded.

Fish ID	Annotation Date	Storage Day	Skin Freshness (0-2)	Eye Freshness (0-2)	Gill Freshness (0-2)	Overall Fish Freshness (0-2)	Note
	DD / MM / YYYY ...... / .... /		Overall: Pinkish colour: Bluish spots: Scales:	Overall: Form: Pupils:	Colour:		
	...... / .... /		Overall: Pinkish colour: Bluish spots: Scales:	Overall: Form: Pupils:	Colour:		
	...... / .... /		Overall: Pinkish colour: Bluish spots: Scales:	Overall: Form: Pupils:	Colour:		

Figure 4.6 The freshness annotation form (designed by Sydney Fish Market)

4.2.2.4 Collection Procedure

As mentioned in 4.2.2.3, the QA staff from Sydney Fish Market is responsible for annotating the freshness scores. For this project, the annotation is conducted in the morning every second day. Once the fish are annotated, the fish images are taken by using the lighting box, as shown in Figure 4.2 (b). This process is known as annotated image data collection. The general dataset collection period can last 14 and more storage days. Figure 4.7 shows the changing trends of fish freshness in terms of overall fish, skin, eye, and gill*. Since the freshness score 1 is a short-period and medium freshness state, the frequency of the annotation for the score 1 was changed from every second day to every day. In this project, only five indices data features are used for the parts of Skin and Eye in Table 4.1.

* note: the gill is currently not used in the model of image processing.

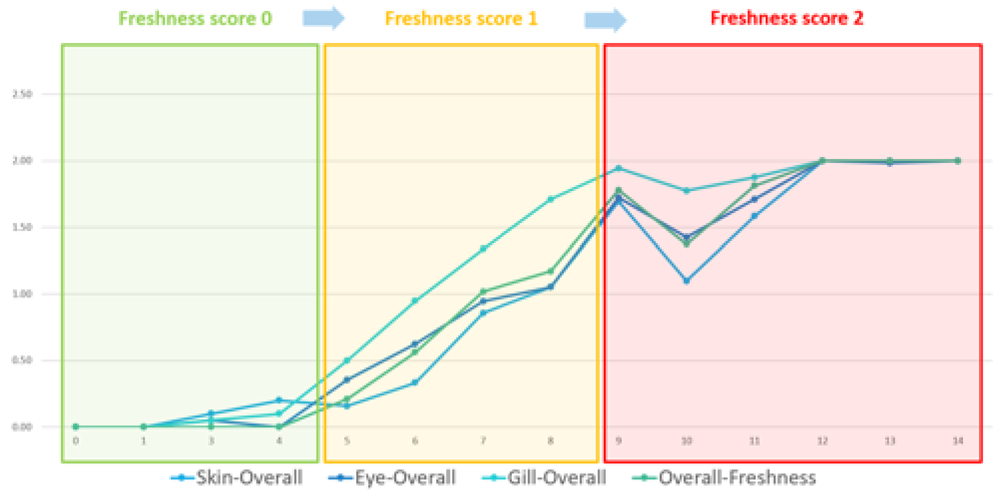


Figure 4.7 Fish freshness changing trends

4.2.3 Algorithm Design

The entire freshness assessment algorithm is designed with three components: snapper detection model, eye-skin detection model, and snapper freshness identification model (see Figure 4.8). There are three processing steps correspondingly. First, the snapper detection model detects and segments the snapper region at the pixel level in the image captured by the mobile camera. Then, the eye-skin detection model detects eye and skin regions by finding a line to separate these two regions. Finally, the detected regions of whole-body, eyes and skin are sent to the snapper freshness identification model to calculate a freshness score for each region, respectively. To align with the table 4.1, the scores are defined with three ranked levels, namely 0,1 and 2. A confidence score is also provided to indicate how confident the model is with its scores on the freshness.

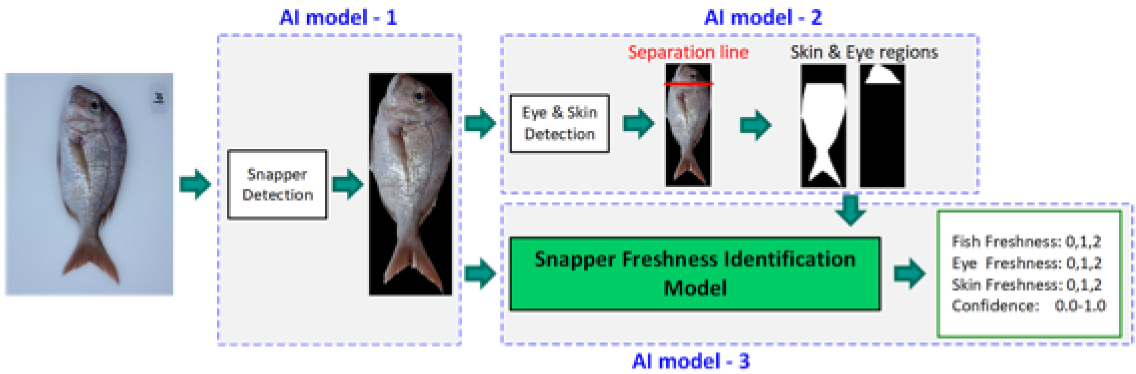


Figure 4.8 Structure of our freshness identification algorithm: AI Models-1, 2 and 3

To explain in detail, as shown in Figure 4.8, three different AI models need to be trained for the three algorithm components, respectively.

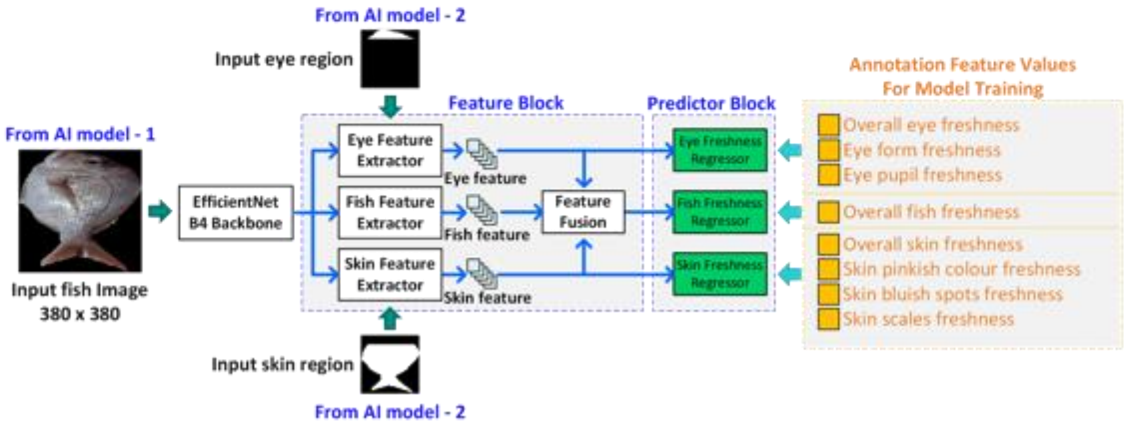
1. The AI model-1 for the snapper detection is trained by referring to the YOLACT [2] but with significant modifications for this project.
2. The AI model-2 for the region separation between eye and skin regions is designed based on a set of images processing algorithms (Principal Component Analysis [5], Histogram Projection [6]) which aims to detect a line to separate the eye and skin regions.

3. The AI model-3 for the snapper freshness identification is the core module. It is divided into a) offline training process and b) online testing process:

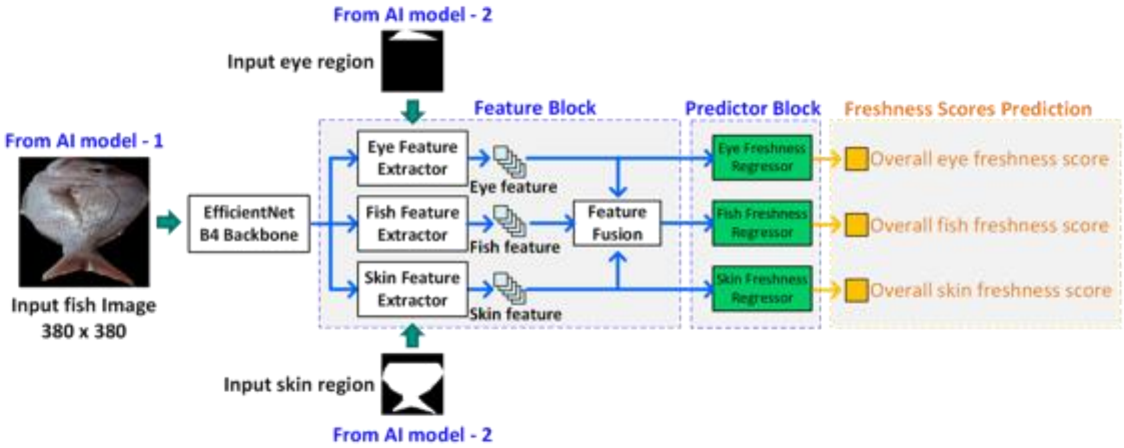
   a) For the offline training process, the AI-based deep learning framework -- B4 backbone of EfficientNet model [1] is adopted with certain modifications. See Figure 4.9 (a), a feature block and a predictor block are specially designed. In this project, the resolution of input images for training is 380 x 380 (pixels by pixels). The fish captured in each image should go through the model-1 of fish detection and model-2 of separate line detection between the eye and skin regions. After these two processes, as shown in Figure 4.9, the input fish image features on eye, skin and whole-body regions will be respectively extracted through the feature-extractor shown by the Feature Block in Figure 4.9 (a). The skin, eye and fused skin/eye/whole-body features will be then input to a regression model as shown by the Predictor Block in Figure 4.9 (a). To train the feature-extractors, regressors and the EfficientNet B4 backbone, the eight annotation features and their values defined in 4.2.2.3 are used as the ground truth to supervise the model training (see the yellow-colour block in Figure 4.9 (a)). Note the annotation feature for gill index is not used. The whole training process is based on the B4 backbone network. The trained regression model will be gradually formed to accurately predict the freshness scores for the eye, skin and fish, respectively.

   b) For the online testing process, the key difference from the training is that there is no fish annotation feature that is manually annotated by Sydney Fish Market, because the online testing is an automated freshness assessment process. See Figure 4.9 (b), the yellow-colour block shows that freshness scores of eye, skin, and fish are predicted. Hence, for each input fish image (380x380), after the processes of model-1 and model-2, the skin, eye and whole-body features, as shown in Figure 4.9 (b), are extracted, then skin, eye and fused skin/eye/whole-body features are input to the regression models for freshness scores prediction including the skin and eye parts, and whole-body, respectively.

   Note: such process of fish image input and final freshness score outputs is known as an end-to-end learning process



(a): AI model-3: the offline training process



(b): AI model-3: the online testing process

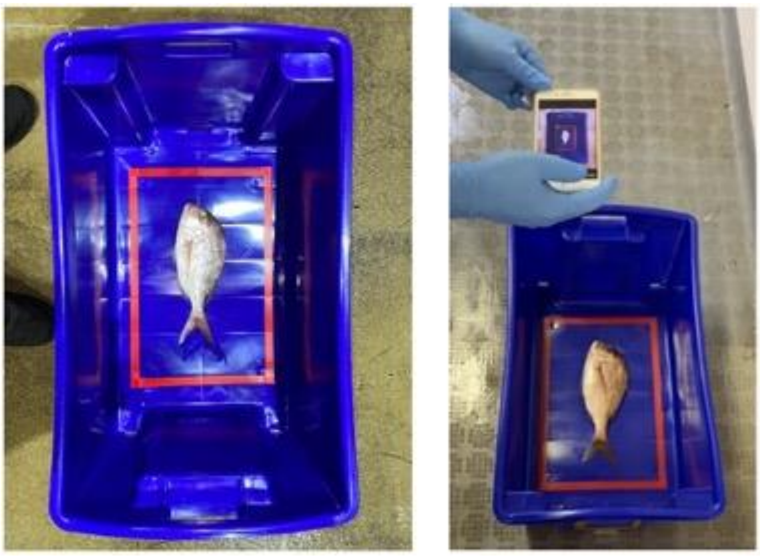
Figure 4.9 The structure of snapper freshness identification model – AI Model 3

4.3 Fish Size Measurement

The technical solution of automated fish size measurement includes three key components: hardware design, test data collection, and algorithm design. Pegrus Auratus Snapper is still the testing species.

4.3.1 Hardware design

To a mobile camera for shooting a fish in the standard blue-box at different high levels, a red-coloured rectangle mark (water-proofing) is stuck to the bottom of the blue-box, and its dimension is 51cm x 27cm. The snapper fish is placed in the middle region of the rectangle mark (see Figure 4.10 (a)), then the mobile is held by an operator to shoot the fish (see Figure 4.10 (b)). The best mobile position is placed when the camera lens surface is parallel with the bottom surface of the blue-box. This can reduce image perspective distortions due to the two surface are not parallelly placed.



(a) (b)

Figure 4.10 The blue-box (a standard container used in Sydney Fish Market for size measurement)

4.3.2 Test data collection

Only test dataset needs to be collected, as the overall algorithm is mainly based on image processing techniques. When every batch of fish arrives, the first thing is to measure fish lengths and then collect test image data (shown by Figure 4.10 (b)) for size measurement. The dataset are collected at the joint lab and auction area in Sydney Fish Market.

4.3.3 Algorithm design

The overall size measurement algorithm is designed based on image processing techniques. It consists of four components: 1) perspective correction model, 2) ruler (red-coloured rectangle mark) detection model, 3) fish detection model, and 4) size calculator (see Figure 4.11).

1) The perspective correction model is designed to remove the distortion caused by the unparallel positioning on the surface planes between the mobile camera and red-coloured rectangle mark. This will cause the distortion on size calculation. To reduce such distortion, first, the four corner points of the rectangle mark are detected under the condition that both surface planes are parallel. Next, during the real measuring, a new set of four corner points are also detected by the mobile camera for the perspective correction. A matrix of perspective transformation between the two sets of corner points is then calculated to correct the perspective distortion on the input image for the ruler and fish detections.
2) The ruler detection model detects the red-coloured rectangle mark and calibrates the size dimension between the ruler and each pixel after the image's perspective is corrected. The rectangle detection process involves detecting rectangle contours from multiple colour channels and attributes of images such as grey, blue, red, hue, saturation, lightness. A shape filter is used to extract high-quality rectangle contours from these candidates. Finally, the actual size (measured by cm) of each pixel on the ruler (red-coloured rectangle mark) is calculated based on these high-quality rectangle contours.
3) The fish detection model detects and segments the fish at image pixel level. It is implemented by the fast instance segmentation model YOLACT [2]. As the YOLACT model generates multiple region candidates for the detected fish, a contour matching algorithm is used to select the top-quality region that is detected.
4) Based on the selected fish region, a Principal Component Analysis (PCA) [5] is applied to all pixel points within the region to obtain a major direction of the fish. Follow the major direction, given the calibration between the pixel and the ruler, the size of the fish can be calculated.

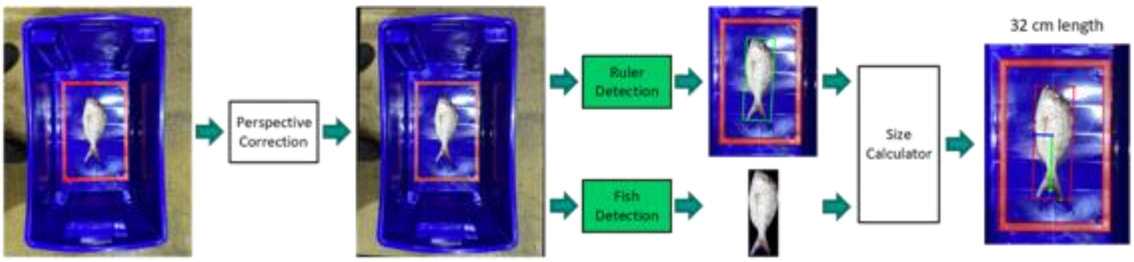


Figure 4.11 Structure of size measurement algorithm

4.4 Fish Species Classification

The technical solution of fish species classification includes three components: hardware design, data collection, and algorithm design. As Pegrus Auratus Snapper is still the testing species, this task is a binary classification between snapper and non-snapper.

4.4.1 Hardware design

Same as the size measurement, the fish is placed at the bottom of the blue-box for snapper/non-snapper species classification (see Figure 4.10).

4.4.2 Data collection

A blue-box-based species dataset should be collected for training and testing the species classification model. Assisted by QA staff, over 20 non-snapper species dataset is collected during the auction period (see small images in Figure 4.12) as a negative dataset. All the images for size measurement can also be marked as positive snapper species samples. For accurate classification, a fish detection model (designed with YOLACT [2] and Grabcut [3]) is applied to crop out unnecessary backgrounds and generate a clean dataset for training the species classification model.

Figure 4.12 Examples of species dataset

4.4.3 Algorithm design

The overall species classification algorithm consists of fish detection model and species classification model (see Figure 4.13). The fish detection model is the same YOLACT model used for size measurement. The species classification model is designed based on the B4 backbone of EfficientNet [1], and the output layer is changed to two classes: the snapper and non-snapper. The input image resolution is also 380x380.

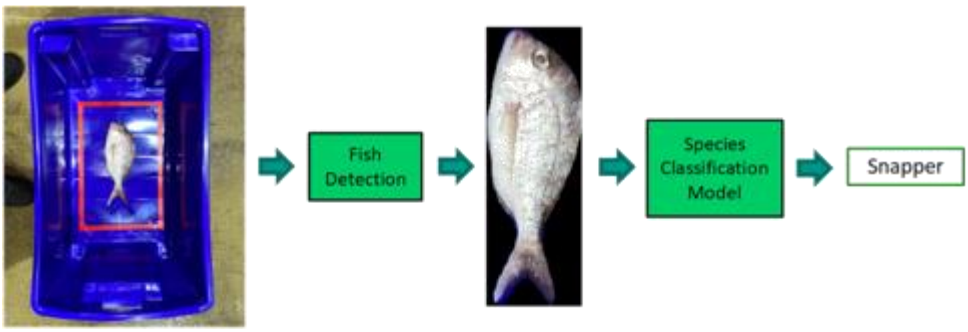


Figure 4.13 Structure of species classification algorithm

4.5 Image processing API System

An image processing API system is developed to provide services for the above three fish tasks. The API system is optimised by GPU with fast processing power. Currently, the system is deployed onto the Alibaba cloud for the integration with the blockchain system and Fisher APP. See Figure 4.14, the blockchain system send requests to the image processing API system by a task ID. Each task ID corresponds to a task type and its corresponding fish image. To achieve high accuracy, multiple images for the same fish are captured and saved into the dedicated URLs. Once the image processing API system receives the task request, it will do the three tasks and send the results back to the blockchain system. Under the task ID (freshness, size, species and freshness/size combined task etc.), the result for each captured image is obtained, the final result is calculated by averaging the results from the multiple captured images. In this project, five images for each fish are captured for the freshness assessment by using the lighting box, and three images are captured for the size auto-measurement and species recognition tasks. All of them are saved into the URLs

Figure 4.15 shows the examples of image processing API results displayed on Fisher APP. As shown in Figure 4.15 (a), two freshness task results are displayed. Take the first row as an example, the overall fish freshness score is 0, the eye freshness score is 0 (indicated by 'E0'), and the skin freshness score is 0 (indicated by 'S0'). The confidence score 0.9 means that the API system is quite confident about the freshness results. In Figure 4.15 (b), two size-species task results are displayed. Take the first row as an example, the species is 'snapper', and the snapper length is 32.9 cm.

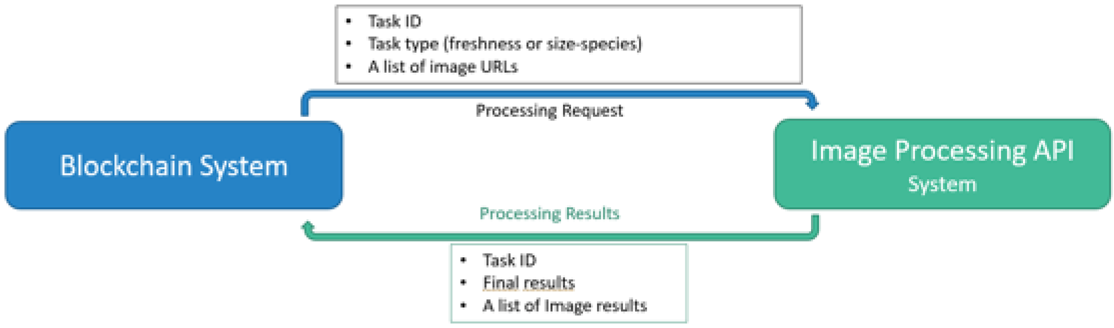


Figure 4.14 Illustration of calling between image processing API algorithm and blockchain

(a) (b)

Figure 4.15 Examples of image processing API results displayed on Fisher APP

5 E-nose

[Steven Su]

The electronic nose system is developed to mimics the human olfactory system to assess freshness based on the smell of the fish. It is capable of reproducing human senses using sensor arrays and pattern recognition technology. Recognition processes are similar to human olfaction and are performed for identification, comparison, quantification, and other applications, including data storage and retrieval.

The key parts of the developed electronic nose system include the sensor array and airflow control system. In this project, based on real experimental data in SFM, we presented the expert sensor array design, fully automated airflow control system, and easy to use user interface to enhance both the assessment efficiency/accuracy and mitigate the environmental disturbance. To well integrate into the APP of BeFAQT mentioned before, we also developed new AI-based future extraction algorithm and adjustable threshold strategy for freshness index prediction.

In the section, we will introduce the developed E-nose based freshness monitoring and assessment system, which include the hardware and interface of the E-nose, the data pre-processing, feature extraction, pattern recognition, and data analysis.

5.1 The design of E-nose and its user interface

The E-nose system is based on, NOS.E, a system which designed to detect and classify different aroma mixtures. The NOS.E system is mainly constructed by the NOS.E instrument, NOS.E user interface and the NOS.E remote server based user interface. The NOS.E instrument is used to detect the odour and transduce the chemical vapours into electrical signals then transmit these signals to the personal computer wirelessly through NOS.E user interface. The remote server based user interface allows the authorised users to review the NOS.E datasets at different locations with the access of internet.

5.1.1 NOS.E Instrument

The NOS.E hardware platform (Fig 5.1.1) consists of the power supply module, the sensor module, the driver module, the communication module, and the microcontroller (MCU, TMS320F28335, 32-bit). The power module provides different isolated power rails for the other parts of the equipment to enable the NOS.E system to work with the driver circuits to satisfy the proposed automated airflow control logic.

Figure 5.1.1: NOS.E equipment.

5.1.1.1 Sensor Selection

The interchangeable sensor array is built with eight commercially available metal oxide gas sensors: TGS 2620, TGS 2602, TGS 2600, TGS 2600, TGS 2603, TGS 2610D, TGS 2611E, and TGS 2612 (FIGARO ENGINEERING INC, Mino, Osaka JAPAN). The target input gases stimulate the gas sensors to generate specific voltage outputs. Then these outputs are collect and pre-processed by the signal acquisition circuits shown in the Fig 5.1.2. An analogue to digital converter (ADC, AD7607, 14-bit) is used to convert these voltage outputs to digital signals which are sent to the MCU for data processing. The MCU completes the tasks such as data acquisition, actuator control, data pre-processing and communicating with the host computer.

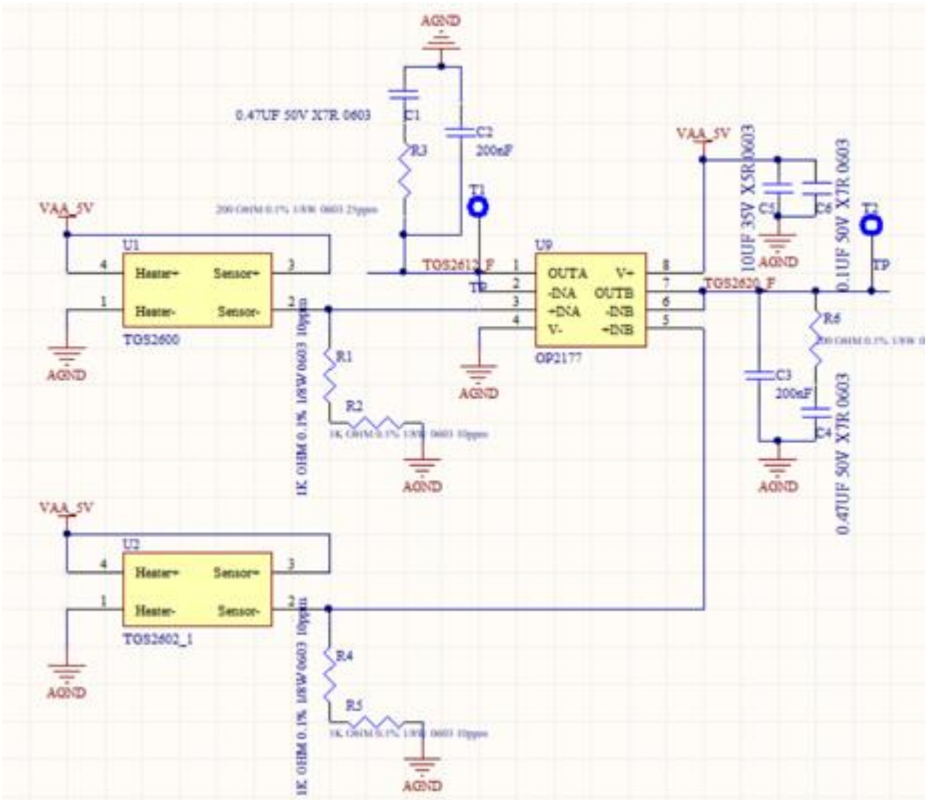


Figure 5.1.2: Sensor Array Data Acquisition Circuits.

5.1.1.2 Chamber Design

The airflow is pumped into the gas mixing and distribution chamber through the gas input port with the airflow velocity from 220mL/min to 2.2L/min. The gas mixing and distribution chamber (shown in Fig 5.1.3) is designed as an air buffer to distribute one input airflow to four airflows.

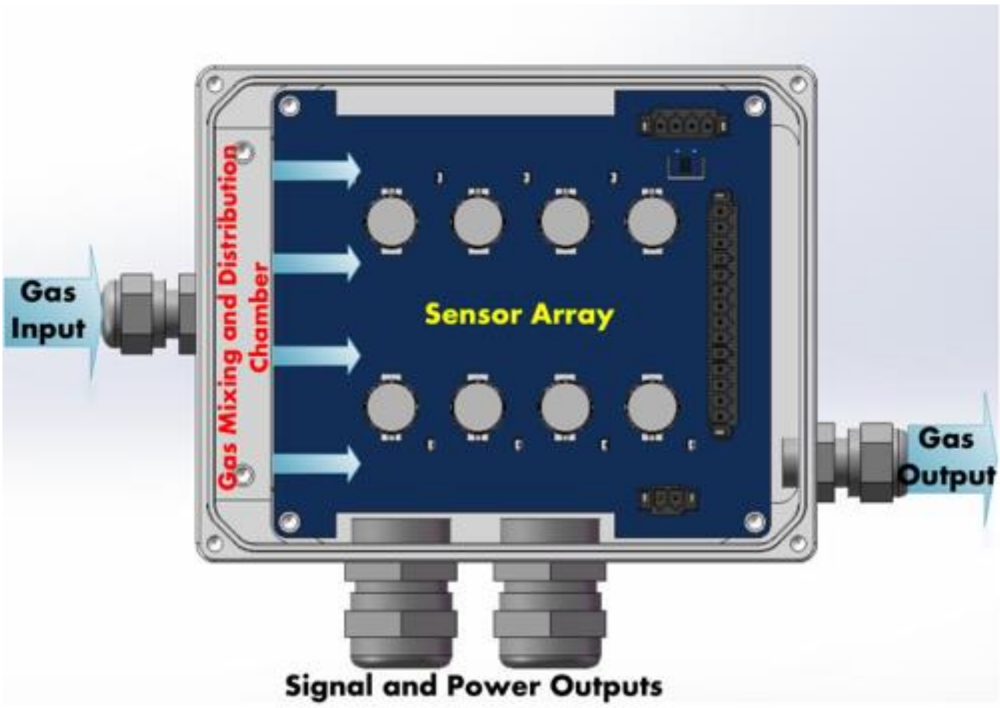


Figure 5.1.3: NOS.E Sensor Chamber.

5.1.1.3 Automated

5.1.1.4 Control Logic

The automated air intake control system in NOS.E does not need the users to configure the test manually for each test. Therefore, it can improve the test efficiency by saving operation time when performing the odour analysis test multiple times. The automated test mode eliminates the incorrect manipulations caused by the manual test, thus improves the data quality and test performance. Eight phases have been designed in the NOS.E control logic. Each working phase has different airflow parameters, which are fixed based on the manual training mode, then preprogrammed into the user interface. Moreover, these airflow parameters are also varied for different applications. Based on the target application selected by the users, the controller will send different commands to control the working status of the actuators. Table. 5.1.1 shows the specific status of the different actuators which are related to the proposed automated control logic. In this table, V1, V2, V3, P1, and P2 represent the control signal of valve I, valve II, valve III, valve IV, pump I and pump II. T1, T2 and T3} are the control phase ID signals sent by the controller. In addition, H indicates the high logic level signal, and L indicates the low logic level signal.

Table 5.1.1: The automated control logic for NOS.E

Phase	V_1	V_2	V_3	P_1	P_1	T_1	T_2	T_3
I	H	L	H	H	H	L	L	L
II	L	L	H	L	H	L	L	H
PAUSE	L	L	L	L	L	L	H	L
III	H	L	H	H	H	L	H	H
IV	L	L	H	L	H	H	L	L
V	L	H	H	H	H	H	L	H
VI	H	L	H	H	H	H	H	L
VII	H	L	H	H	H	H	H	H

Note: H: High logic level signal; L: Low logic level signal.

5.1.2 NOS.E User Interface

The NOS.E user interface (Fig 5.1.4) is used to configure the NOS.E equipment. This user interface is based on the visual studio code platform and the Visual Basic (VB) programming languages. It can also send the commands to control the different actuators and show the real-time working status of these actuators. The user interface is also used to record, store, and analyse the data by using related widgets and commands. The output wave-forms of gas sensors is displayed to the user in real time. The collected odour data is stored on the local disk in the text format. Key features of the odour data are extracted and shown to the user in graph.

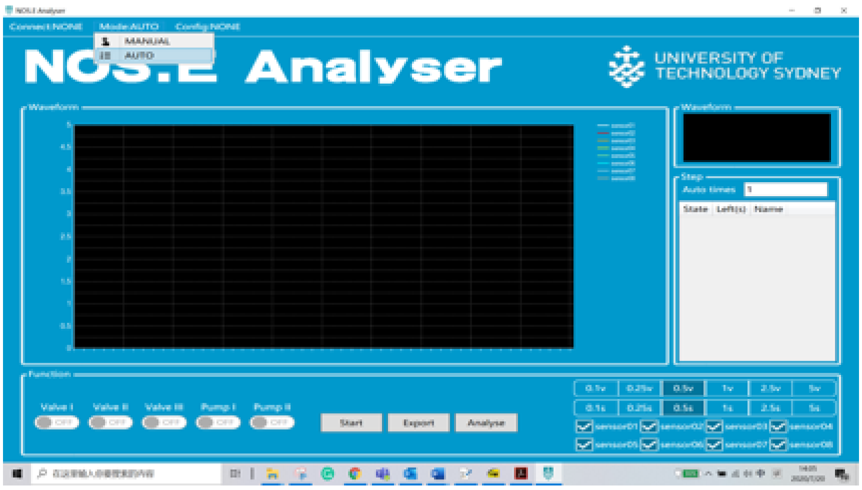


Figure 5.1.4: NOS.E User Interface.

As shown in Fig 5.1.5, the users can set different parameters for required working phase by adding the new row/ deleting the last row; the users can also import the configuration files from the config folder. These configuration information can be exported once all the parameters are fixed.

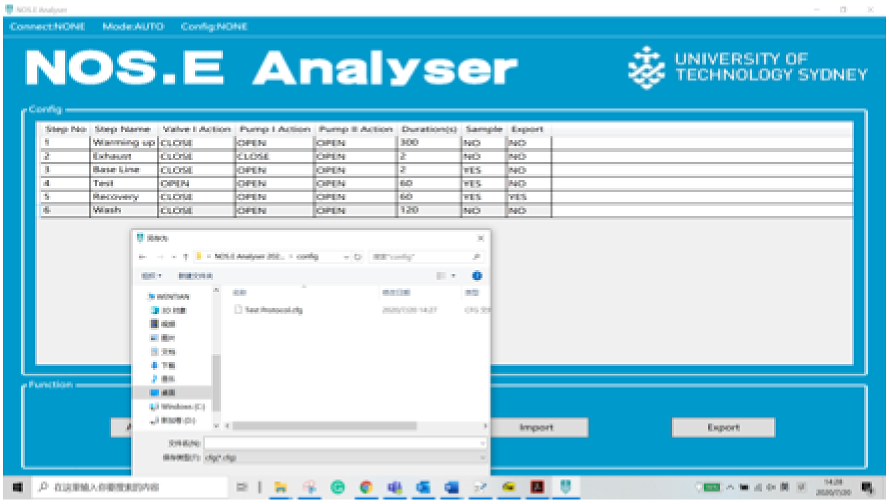


Figure 5.1.5: NOS.E Test Protocol Configuration.

5.2 The developed freshness assessment algorithms

This section introduces the data processing procedure for E-nose, including data pre-processing techniques, feature extraction algorithms, freshness assessment methods, and the integration with the BeFAQT system. The roadmap of E-nose fish assessment is illustrated in Fig. **5.2.**1.

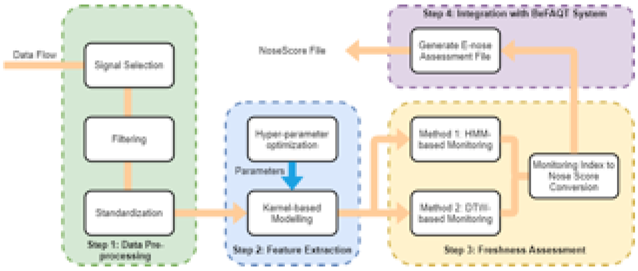


Figure 5.2.1: Roadmap of E-nose fish freshness assessment

5.2.1 E-nose Signal Pre-processing

This section introduces signal pre-processing procedure used in the e-nose signal analysis, which includes three steps: signal selection, filtering, and standardization.

5.2.1.1 Signal Selection

One measurement (sniffing) of the E-nose can be separated into four basic stages as shown in Table 5.2.1. The most useful information is usually extracted from the second stages, i.e. the test stage. Hence, we only select the sensor's signal at the duration 1 to 200 s. The rest signal is discarded in case of occupying a lot of computer resources.

Table 5.2.1: E-nose Operation Parameter

Procedure	Operation	Duration (s)
1	Baseline Setup Time	[0 2)
2	Test Time	[2 122)
3	Baseline Recovery Time	[122 242)

4	Chamber Washing Time	[242 482]

5.2.1.2 Filtering

The subsequent feature extraction algorithm has a good performance in dealing with noise-contaminated signals except the outlier. Hence, to reduce the influence of outlier, median filter is adopted. The window length is optimized as 3 in our experiment. A representative example of filtering result is shown in Fig. 5.2.2.

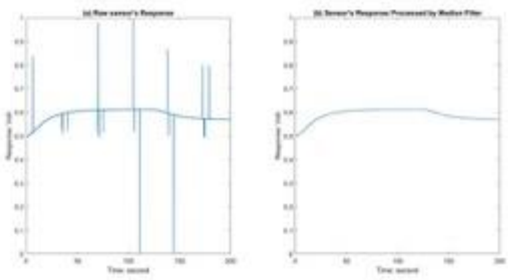


Figure 5.2.2: Representative example of median filtering. (a) Raw sensor's response. The spikes in the figure are outliers. (b) Sensor's response processed by median filter. After filtering, the signal became smooth.

5.2.1.3 Standardization

After median filtering, standardization is adopted to reduce the influence of sensor drift and compensate for the fluctuation in concentration, as follows:

$$y_s(t) = \frac{x_s(t) - \mathbf{mean}(x_s(t))}{\mathbf{std}(x_s(t))}, s = 1, \dots, S, t = 1, \dots, T, \qquad (1)$$

where $x_s(t)$ denotes the s-th sensor's response, and $y_s(t)$ the corresponding standardized signal. S is the number of gas sensors selected. T is the length of sensor's response.

5.2.2 Stable Feature Extraction Using Kernel-based Modelling

This section introduces the proposed feature extraction algorithms for e-nose signals.

5.2.2.1 Mechanism: Modelling-based Features for E-nose

The E-nose can be regarded as a system. As illustrated in Fig. 5.2.3, we assume that the system input is a unit step signal, where 1 means that the odour source has been exposed to the E-nose, and 0 is not. However, the system output is subjected to divergence from the step input by interfering factors, including the properties of gas molecules, airflow circuit, sensors, environment temperature, and environment relative humidity (RH). Different interfering factors result in different systems. When environmental and device operation parameters are well-regulated, the only interfering factor is the properties of gas molecules. Gas molecules can therefore be expressed by system parameters. The modelling-based feature representations is developed accordingly.

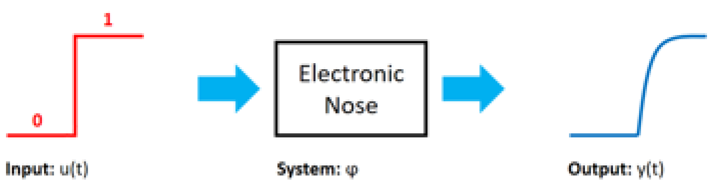


Figure 5.2.3: Explanation of modelling-based feature representation for smell.

5.2.2.2 Kernel-based Modelling

Here, impulse response (IR) model is selected to represent the system. The reason is as follows: i) IR model is a non-parametric model. The order of the system is no need to pre-defined anymore; ii) IR model takes both the current input and the previous behavior of the system into consideration, and therefore, can extract more features.

Let $y_s(t)$ be the standardized sensor's response, and $u_s(t)$ be the corresponding assumed unit step input. φ_s represents the impulse response of the system. Hence, their relationship can be expressed as:

$$y_s(t) = (\varphi_s * u_s)(t) + \varepsilon_s(t), \tag{2}$$

where $\varepsilon_s(t)$ represents the noise obeying the Gaussian distribution. $*$ denotes the convolution operation. $u_s(t)$ can be expressed into the form of Toeplitz matrix with 0 paddings, as follows:

$$\mathbf{U}_s = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 1 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & \cdots & 1 \end{bmatrix} \in \mathbb{R}^{T\times M}. \tag{3}$$

Accordingly, (2) can be vectorized as:

$$y_s = \mathbf{U}_s \varphi_s + \varepsilon_s, \tag{4}$$

where $y_s = [y_s(1), y_s(2), \dots, y_s(T)]^{\mathrm{T}} \in \mathbb{R}^T$, $\varepsilon_s = [\varepsilon_s(1), \varepsilon_s(2), \dots, \varepsilon_s(T)]^{\mathrm{T}} \in \mathbb{R}^T$, and $\varphi_s = [\varphi_s(1), \varphi_s(2), \dots, \varphi_s(M)]^{\mathrm{T}} \in \mathbb{R}^M$. M is the order of the system. In this case, we set $M = T$.

However, deconvolution from (4) is an ill-posed problem. Hence, a kernel-based regularization term is added to provide additional constraints. The impulse response can be calculated as:

$$\varphi_s = \underset{\varphi_s}{\mathbf{argmin}} \|y_s - \mathbf{U}_s\varphi_s\|_2^2 + \sigma^2 \varphi_s^{\mathrm{T}} \mathbf{K}^{-1} \varphi_s \tag{5a}$$

$$= \left(\mathbf{K}\mathbf{U}_s{}^{\mathrm{T}}\mathbf{U}_s + \sigma^2 \mathbf{I}\right)^{-1} \mathbf{K}\mathbf{U}_s{}^{\mathrm{T}} y_s, \tag{5b}$$

where σ^2 denotes the variance of the system noise. $\mathbf{K} = [k\langle i,j\rangle] \in \mathbb{R}^{M\times M}$ is kernel matrix. In this work, we adopt the stable spline (SS) kernel, which can be calculated as:

$$k\langle i,j\rangle = \frac{c}{2}\left(\mathbf{exp}\{-\beta(i+j) - \beta\mathbf{max}\,(i,j)\} - \frac{1}{3}\mathbf{exp}\{3\beta\mathbf{max}\,(i,j)\}\right), \tag{6}$$

where $c, \beta > 0$ are hyper-parameters of the kernel function.

The solution of (5b) is applied as the feature of the target smell. The proposed feature extraction method has a stable performance in resistance to noise, as an example illustrated in Fig. 5.2.4. Although the observation is contaminated by different noises, the re-constructed signal is the same.

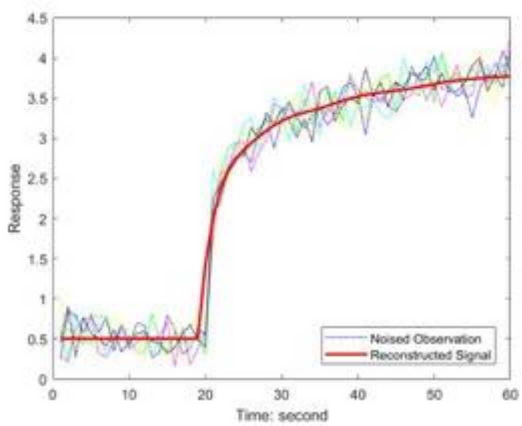


Figure 5.2.4: Performance of proposed feature extraction methods. The dash lines represent noised observation of gas sensor to the same analyte.The red solid line represents the re-constructed signal using the extracted features. Although the observations are different, their features are the same.

5.2.2.3 Kernel Parameter Optimization

The selection of the hyper-parameter significantly influence the performance of the proposed method. From our previous study, an experimental selection for β is in the range of [0.9 1]. Here, an optimization method for kernel parameters is proposed as follows:

$$(c^*, \beta^*) = \underset{c>0, \beta\in[0.9\ 1]}{\mathbf{argmax}} \frac{1}{T \cdot S} \sum_{t\in T} \sum_{s\in S} \left(1 - \frac{\|y_s(t) - \hat{y_s}(t|c,\beta)\|_2^2}{\left\| y_s(t) - \frac{1}{T}\sum_{t\in T} y_s(t) \right\|_2^2} + \frac{\mathbf{Ent}(\varphi_s|c,\beta)}{2\mathbf{log}(T)} \right), \quad (7)$$

where $\mathbf{Ent}(\varphi_s|c,\beta)$ is the information entropy of φ_s, which can be calculated as:

$$\mathbf{Ent}(\varphi_s|c,\beta) = \frac{|\varphi_s(m|c,\beta)|}{\sum_{m\in M}|\varphi_s(m|c,\beta)|}. \quad (8)$$

This function can be optimized via heuristic searching algorithms, such as Genetic algorithm (GA), Particle Swarm Optimization (PSO), or DIRECT algorithm.

5.2.3 Australia Snapper Freshness Tracking

This section introduces the mechanism of freshness monitoring and two proposed algorithms for tracking the freshness change of Australia snapper.

5.2.3.1 Mechanism: Freshness Monitoring as One-class classification

The training of a smell model need hundreds to thousands of training samples. It is impossible for an E-nose to train models for every rotten smells, since the reasons that cause spoilage are uncountable. Even if it is possible, the cost will be very expensive, since one measurement for an E-nose takes a long time. To avoid the problem over complicated, we can simplify it by one-class classification, i.e. only identifying the fresh smell. As illustrated in Fig. 5.2.5, the model of fresh samples can be a probability distribution, the monitoring is made by measuring the likelihood that the test sample smell is generated by the fresh model.

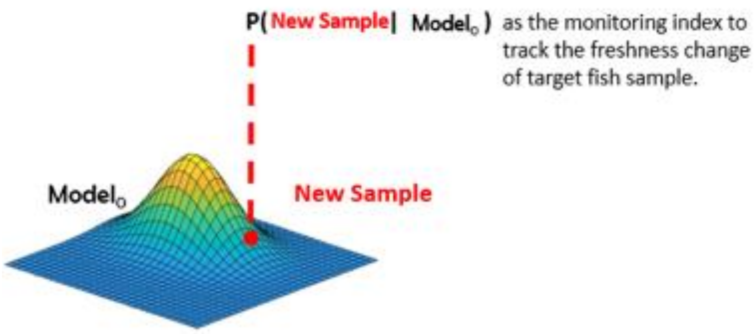


Figure 5.2.5: Explanation of freshness monitoring as one-class classification. Model$_0$ denotes the probability distribution trained only by fresh samples. The red dot denotes a test sample. P(New sample | Model$_0$) describes the likelihood of the new sample is generated from the distribution. If the probability is high, the sample is considered as fresh.

5.2.3.2 Probability-based Freshness Monitoring Using Hidden Markov Models

The distribution of fresh samples is learned using a classical statistic tool, i.e. Hidden Markov Model (HMM). This model can be trained using the Segmental Rapid Centroid Estimation (RCE)-based Intialization with Baum-Welch Algorithm. The use of RCE algorithm is to ensure a stable training result. Once the fresh model (model 0) is obtained, freshness evaluation can be made using the Forward-Backward Algorithm. For a given sample φ, the monitoring index $\mathrm{MI_{HMM}}$ is defined as the output of the Forward-Backward Algorithm, i.e. the log-likelihood of the sample:

$$\mathrm{MI_{HMM}}(\varphi) = \mathbf{log}(\mathrm{P}(\varphi|\mathrm{modle_0})). \quad (9)$$

The sample is considered to be fresh when the $\mathrm{MI_{HMM}}$ is close to 0.

The flowchart of HMM-based monitoring method is shown in Fig. 5.2.6.

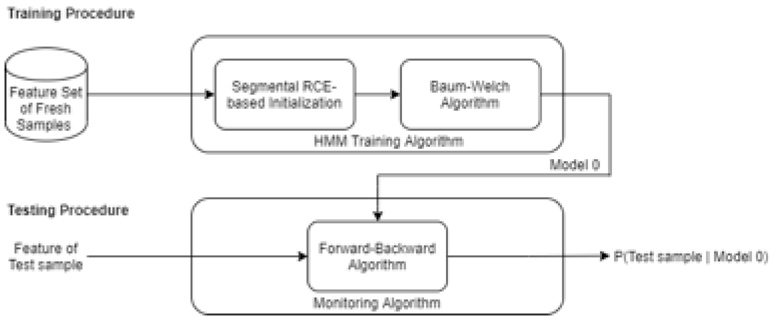


Figure 5.2.6: Flowchart of HMM-based freshness monitoring algorithm. In the training procedure, the input of the HMM training algorithm is the feature set of fresh Australia snapper samples. The output is the learned distribution, model_0. In the testing procedure, the inputs of the monitoring algorithm are both the feature vector of target sample and the learned distribution Model_0. The output is the likelihood P(Test sample | Model_0).

5.2.3.3 Distance-based Freshness Monitoring Using Dynamic Time Wrapping

A simpler implementation for freshness monitoring is using a distance measure. Since the extracted feature is a time series, the Dynamic Time Wrapping (DTW) algorithm is adopted.

The DTW-based monitoring index is defined as the average of pairwise DTW measure of the training set, which is calculated as:

$$\mathrm{MI}_{\mathrm{DTW}}(\varphi) = \frac{1}{N}\sum_{n\in N} \mathbf{dist}_{\mathbf{DTW}}(\varphi, \varphi_0^{(n)}), \tag{10}$$

where N is the sample size of the training set, and $\varphi_0^{(n)}$ is the n-th training sample. A small $\mathrm{MI}_{\mathrm{DTW}}$ indicates a fresh sample.

5.2.3.4 Conversion From Monitoring Index to Nose Score

The probability measure can be changed to distance measure by $\mathrm{MI} = |\mathrm{MI}_{\mathrm{HMM}}|$. The smaller the MI, the fresher the sample. The thresholds to separate freshness level 0, 1, and 2 is a statistical result of our previous experiments as th_0, th_1, and th_2, respectively. Since our method is based on a one-class classification model, additional threshold th_3 is also given as the upper bound.

When all the thresholds are defined, the conversion from MI to confidence is given by:

$$\mathrm{confi}_i(\varphi) = \frac{\mathbf{exp}(p_i(\varphi))}{\sum_{i=0}^{2}\mathbf{exp}(p_i(\varphi))}, i = 0,1,2, \tag{11}$$

where p_i is defined as:

$$p_i(\varphi) = \frac{\frac{1}{|\mathrm{MI}(\varphi) - l_i|}}{\sum_{i=0}^{2}\frac{1}{|\mathrm{MI}(\varphi) - l_i|}}, i = 0,1,2, \tag{12}$$

where $l_i = \frac{\mathrm{th}_i + \mathrm{th}_{i+1}}{2}, i = 0,1,2$. The Nose Score is given by:

$$\mathrm{NoseScore}(\varphi) = \sum_{i=0}^{2} i \times \mathrm{confi}_i(\varphi). \tag{13}$$

5.2.4 Integration with the BeFAQT System

The assessment output of the E-nose is served as a JSON file recorded the result of five measurements for the BeFAQT system, as an example shown in Fig. **5.2.**7. The report is stored in the address, Enose\[BOX ID]\[UnixTimeStamp], as noseScore.txt.


```
{
    "noseScore": 0.7,
    "confidence": 0.7,
    "time": "2020-06-01 10:49:14",
    "latitude": -33.872901,
    "longitude": 151.192333,
    "resultPerTest":[
        {
            "noseScore": 0.5,
            "confidence": 0.9,
            "sensingData": "034557944/1590972494/test1.txt"
        },
        {
            "noseScore": 0.5,
            "confidence": 0.5,
            "sensingData": "034557944/1590972494/test2.txt"
        },
        {
            "noseScore": 0.5,
            "confidence": 0.9,
            "sensingData": "034557944/1590972494/test3.txt"
        },
        {
            "noseScore": 0.5,
            "confidence": 0.9,
            "sensingData": "034557944/1590972494/test4.txt"
        },
        {
            "noseScore": 1.5,
            "confidence": 0.4,
            "sensingData": "034557944/1590972494/test5.txt"
        }
    ]
}
```


Figure 5.2.7: Representative example of the E-nose assessment. The result of five measurements are stored in noseScore.json file. The overall noseScore and confidence is the average of five measurements.

5.3 Experiments and Results

In this section, we first introduce the experimental protocols and the experiments, and then discuss experimental results and the adjustable thresholds for the Freshness Index assessment.

5.3.1 Experimental protocols and experiments

The SFM experts showed us how to choose the fish container to maintain the temperature inside. Also, according to the actual test scenario, the foam cold box with a top cover is recommended for the electronic nose test. This can prolong the test during the serving (gathering more useful information during a test) and, most importantly, can reduce the rate of melting of the ice inside the container.

After discussing it with the SFM experts, it is found that the mucus from the fish skin is also used to analyse the freshness quality of the fish. Based on this idea, we proposed the second e-nose test methods for the fish freshness analysis test.

Based on the domain knowledge input from SFM experts, SFM training sessions, and e-nose dry-run tests at UTS lab, e-nose team had completed the formal test protocol for the fish freshness e-nose test. In this protocol, two different odour test methods were proposed for this project.

The two experimental protocols are the fish box-based protocol as shown in Fig. 5.3.1 and the headspace bottle-based protocol as shown in Fig. 5.3.2. The first is to "smell" the snapper stored in a foam cooler box. The second is to detect the smell of snapper mucus adhering to the sampling cotton.

Figure 5.3.1: The fish box based experimental protocol.

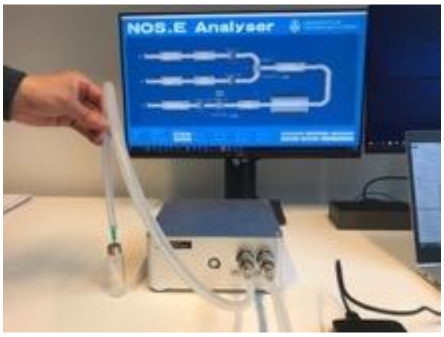


Figure 5.3.2: The head-space bottle based experimental protocol.

5.3.2 Results and Discussion

Based on the proposed protocols, we completed several round of experiments. The experimental results are summarized in the following subsections.

5.3.2.1 Result for fishing box based experimental protocol

In the first stage of the project, we spent a lot of time and energy on the experiments by placing the fish sample in a fish box filled with ice (i.e., experimental protocol 1).

Based on the experimental data, the feature has been extracted with a set of statistical features including Mean, Max, Standard Deviation, Variance, Skewness, Kurtosis, Integral and Mean differential coefficient value. The Distance in the sense of Dynamic Time Warping (DTW) was performed and this Distance was added as another feature. The ratio of the training set and test set is 70:30 respectively. Based on PCA classifier by mainly using three sensors (Sensor Number 3, 6, and 7), therefore, in total 28 features.

The training and testing results are summarized as follows:

The training accuracy is 84.5%, and the test accuracy is 73.2% (see Table 5.3.1 for details).

Table 5.3.1: Accuracies and results for Test Dataset

	Index 0 ***Unspoiled***	**Index 1** ***Acceptable***	**Index 2** ***Spoiled***	**Overall**
No. Correct Predicted Values	13	15	13	41
No. Expected Predicted Values	15	22	19	56
Accuracy	86.7%	68.2%	68.4%	73.2%

5.3.2.2 Result for head-space bottle based experimental protocol

The testing results for the fish box based protocol is low. The problem regarding this experimental setting is due to the fact that the gas sensors will become less sensitive when the temperature decreased. Also, the ice will decrease the temperature and generate a temperature field to disturbance the response of the gas sensors. Thereafter, we abandoned this type of experimental protocol, but we accumulated a lot of data for exploring the influences of temperature variations.

In the late stage, we concentrate on the headspace bottle based protocol. However, due to various limitations, these experimental data could not be labelled in terms of Freshness Index. However, we monitored the fish sample by using E-nose day by day.

We also found the proposed two freshness-monitoring methods are able to depict the fish sample's freshness by calculating either the likelihood or the DTW (Dynamic Time Warping) distance to the fresh samples. However, as the DTW method is computational more efficient, in later discussion, we only show the result in terms of DTW distance.

After numerical analysis, we found in the first 5-6 days (see Fig.5.3.4) of the responses of E-nose are not significant (the DTW distance is less than 0.1), and the DTW distance does not increase with time.

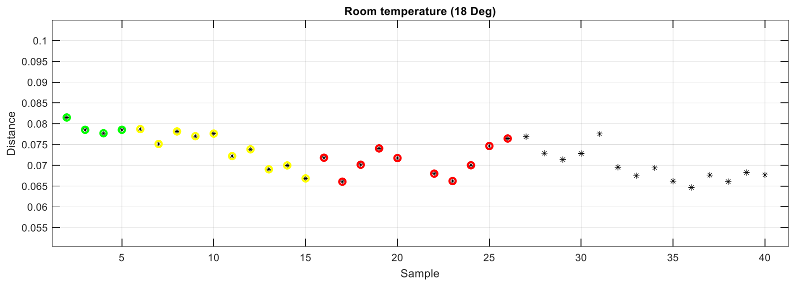


Figure 5.3.3: The DTW distance of early stage samples (less than 6 days) under the head-space bottle based protocol in room temperature.

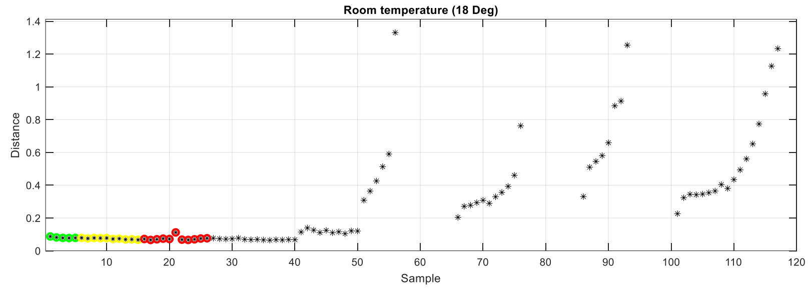


Figure 5.3.4: The DTW distance of fish samples within 10 days under the head-space bottle based protocol.

5.3.2.3 Summary for temperature controlled experimental results

Later, to investigate the influence of environmental temperature, we had done several head-space bottle based experiments from around day 2 to day 9. It was observed that up to day 6, the responses of gas sensors have no significant changes (observed random responses in the first 6 days). After day 6, the E-nose responses start to become significant.

In order to further observe the subtle changes in the first 5 days, we designed and implemented temperature-controlled experiments.

The main purpose of the temperature-controlled experiments are as follows:

1. Test the hypothesis that the gas sensors will become more sensitive for the heated samples during the first 6 days.

   Experimental results did not support this hypothesis as in the first 6 days, the response of the E-nose is still insignificant (see Fig. 5.3.6) at 50 deg.

1. Explore the influence of temperature change on the gas sensor, so that in the future, we can establish a temperature model to compensate the temperature disturbances.

   However, to build this model may require a large number of experiments and need to repeat the modelling procedure for different E-nose.

Instead, we develop a pre-calibration protocol that can partly compensate for the influence of environment variations. In this way, we do not need temperature control and fresh air cylinder. The main idea of the pre-calibration protocol is to perform extra calibration experiments immediately before the assessment. Instead of calculating the distance to the previously stored data of fresh fish, we calculate the distance to these extra calibration experimental data. By doing so, some of the common environmental disturbance can be counteracted.

Figure 5.3.5: Temperature controlled experiments under the head-space based experimental protocol.

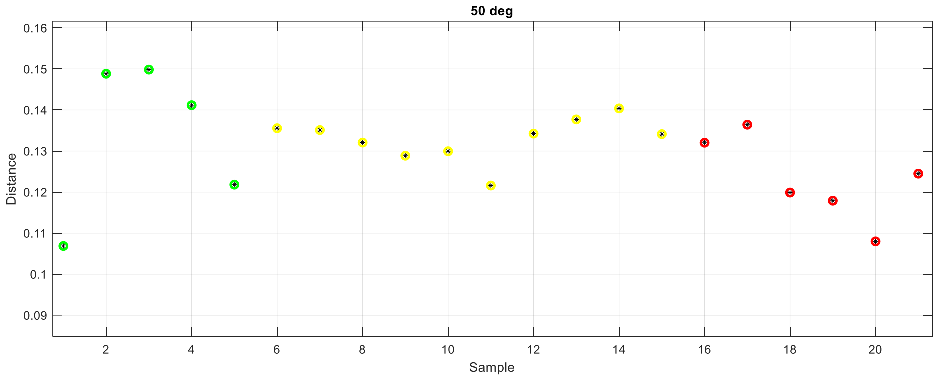


Figure 5.3.6: The DTW distance of fish samples within 5 days under the controlled temperature of 50 ºC.

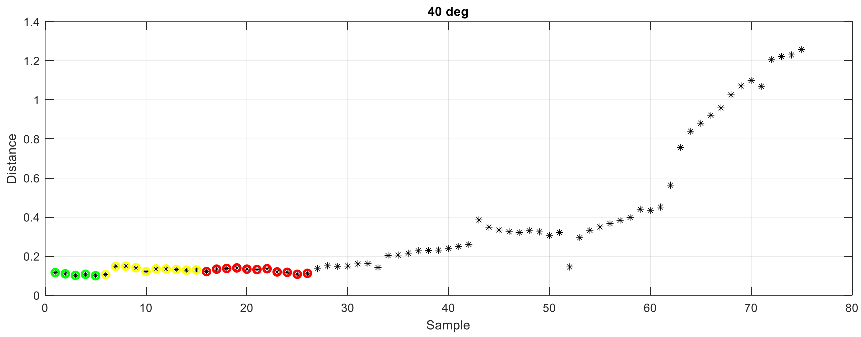


Figure 5.3.7: The DTW distance of fish samples within 10 days under the controlled temperature of 40 ºC.

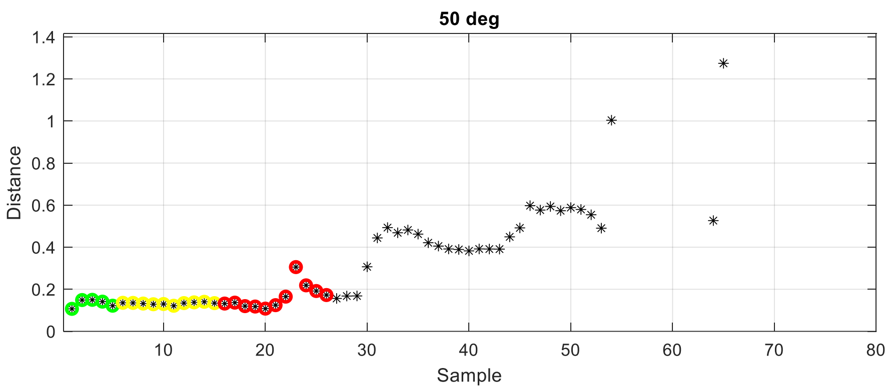


Figure 5.3.8: The DTW distance of fish samples within 10 days under the controlled temperature of 50 ºC.

We did experiments under the controlled temperature by using Protocol 2. It is observed that when temperature increase, the level of response increased after day 6. However, the value of increase is not significant as shown in Fig. 5.3.7 (40 deg) and Fig. 5.3.8 (50 deg), especially in the first 5 days.

5.3.3 Adjustable threshold for freshness Index Assessment

After addressing the environmental disturbance, we consider aligning the E-nose based Freshness Index with the index annotated by SFM expert. Based on our previous experience, the key and challenging issue is to discriminate fish freshness from Index 1 to Index 0, as Index 2 is rarely encountered and is relative easier to be verified by simple inspection.

Also, to cross-validate the standard, for e-nose (maybe also for block-chain and e-eye), the most important parameter is the thresholds of Freshness Index 1. We particularly collected about 10 fish samples, annotated as Index 1 by SFM expert, to estimate the thresholds of Freshness Index 1. We have also done several round experiments for fishes from day 2 to day 9 (without annotation see Fig. 5.3.7); from these experiments, we can also detect the critical value from which the response of e-nose starts to become more significant. This critical value gives the indication, for E-nose model, to find the thresholds of Index 1. To identify a statistically justified threshold for the E-nose model, we still need more annotated experiments. In the future, if we still have a chance for to acquire more annotated snappers with the IoT tracking box and E-eye, we are very happy to use E-nose to collect more annotated experimental data.

As metioned befor, in the later stage, to investigate Index 1 threshold, we selected about 10 Index 1 fishes annotated by SFM experts to do the experiments under the new improved protocol. According to the experimental results, we can roughly determine the thresholds of 0 vs 1 and 1 vs 2, that is, we can roughly estimate the original score range of Index 1 (DTW distance to fresh air response).

Certainly, more experiments are needed to statistically estimate the threshold. It was also observed that the E-nose responses to index 1 fish are all significant, and we use the minimum original score as the threshold for 0 vs 1 and the maximum score for 1 vs 2. In the future, users can estimate more accurate thresholds when there are more expert annotated fish being analysed by the proposed experimental protocol.

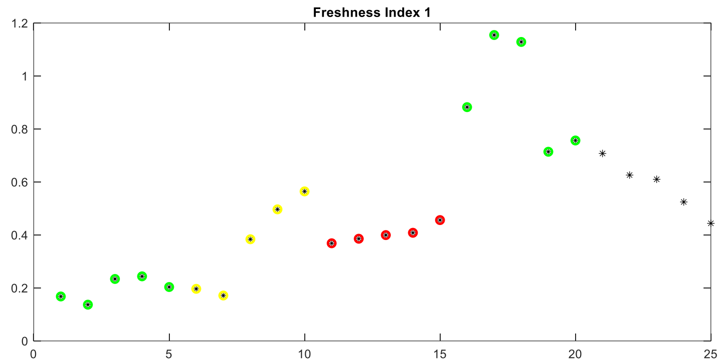


Figure 5.3.9: The ranges of the DTW distance of fish samples with Index 1 annotated by SFM experts.

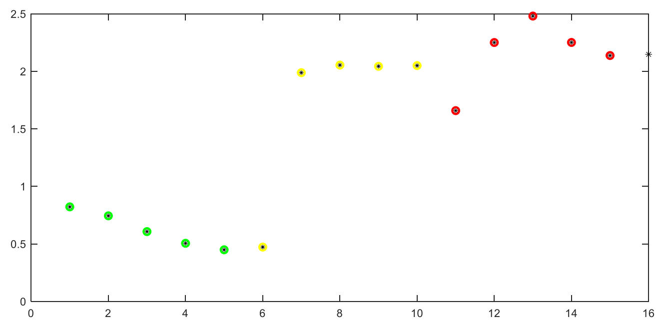


Figure 5.3.10: The DTW distance of randomly selected fish samples with Index 1, 1.5 and 2.

In summary, if we set the threshold Index 0 vs Index 1 as 0.1 (in terms of the DTW distance) and the threshold Index 1 vs Index 2 as 2.5 then the accuracy of freshness index prediction will be much better than 73.2% (the classification accuracy of fish box based protocol).

6 BeFAQT Trading Platform

[Ren Ping Liu]

The BeFAQT Online Trading Platform integrates mobile App, IoT tracking, sensing, E-eye and E-nose results into one platform. The provenance, tracking, and freshness assessment data are secured by Blockchain. The BeFAQT platform is developed as a full-fledged online trading platform, where consumers can browse and buy seafood products. Store owners can manage seafood products and consumer orders through shop management pages.

The BeFAQT platform is developed in MERN stack:

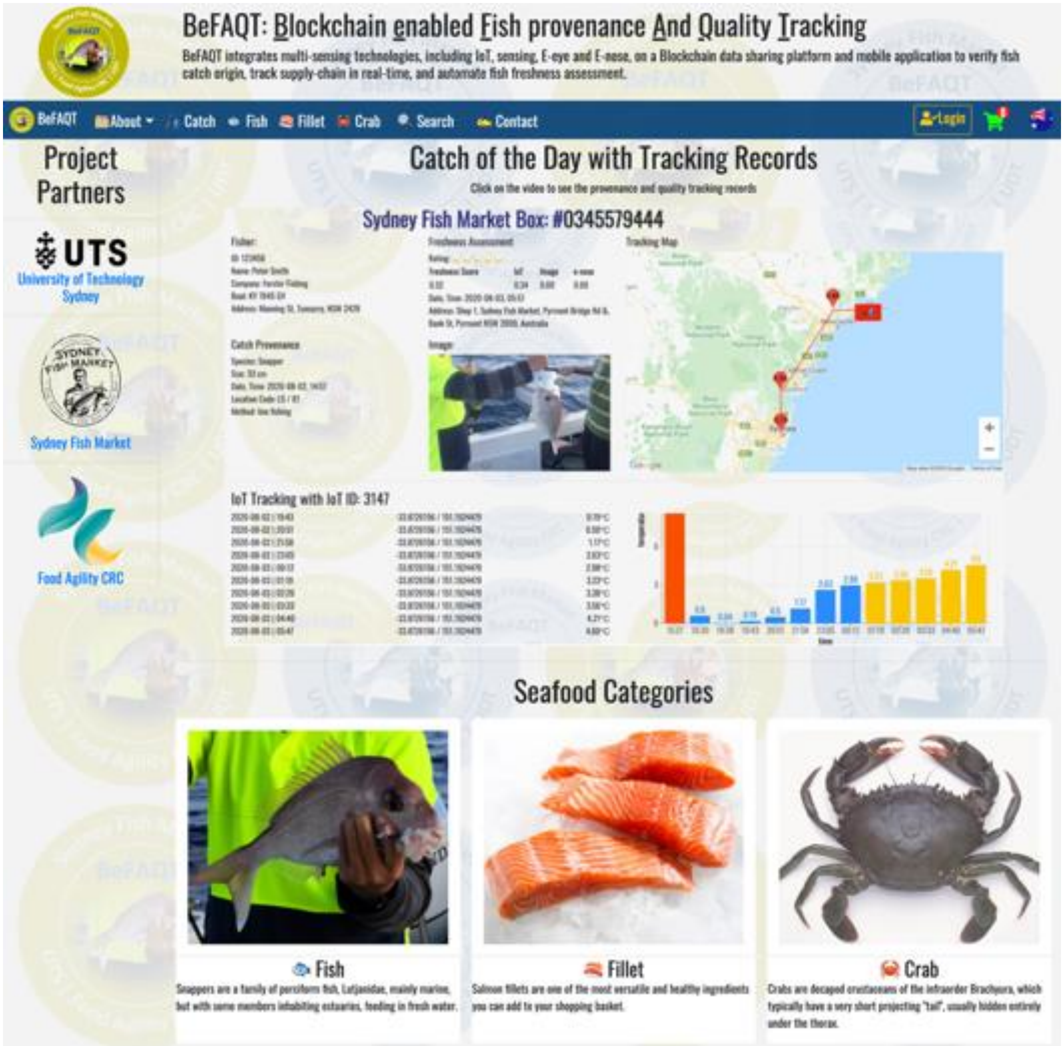
- React as frontend framework
- Node.js and Express as backend framework
- MongoDB as the database system

6.1 Trading Platform

The BeFAQT trading platform can be accessed here:

https://www.befaqt.com/

In the front page, it has the Blockchain secured "Catch of the Day with Tracking Records" and Seafood Categories for online trading.



6.2 Catch of the Day with Tracking Records

The “Catch of the Day with Tracking Records” includes the following data:

- Catch provenance data via Fisherman App,
- Supply chain tracking data via IoT and sensors
- E-eye fish quality assessment data
- E-nose fish quality assessment data

These Blockchain secured data are served from a RESTful API at:

https://api.befaqt.com/api/sfm/data

the data is served as a JSON file.


```
status:                 200
message:                "success"
▾ content:
    boxID:              "0345579444"
  ▾ fisher:
      traderID:         "123456"
      traderName:       "Peter Smith"
      companyName:      "Forster Fishing"
      boat:             "KY 7645 GV"
      address:          "Manning St, Tuncurry, NSW 2428"
  ▾ catchProv:
      time:             "2020-08-02 14:57:09"
      boat:             "KY 7645 GV"
      latitude:         -32.821074
      longitude:        152.110708
      locationCodeLat:  "L5"
      locationCodeLong: "81"
      method:           "line"
    ▾ img:              "https://oss.befaqt.com/sfm_tracer/fish_photos/Catch.jpg"
      species:          "Snapper"
      size:             "33 cm"
      note:             "line fishing"
    ▾ txHash:           "0x3fcb939255c12b54c25383fefa3ff2227618163dcdbd5fbb482d7d4962b2f4f0"
  ▾ iotResult:
      operator:         "UTS-IOT-XW"
      iotScore:         0.33826
      confidence:       1
      time:             "2020-08-03 05:47:38"
      latitude:         -33.8726156
      longitude:        151.1924479
    ▾ iotTracking:
      ▾ 0:
          time:         "2020-08-02 15:27:09"
          latitude:     -32.7783244
          longitude:    152.1003581
          iotID:        "3147"
          temperature:  11.6875
        ▾ txHash:       "0x3fcb939255c12b54c25383fefa3ff2227618163dcdbd5fbb482d7d4962b2f501"
      ▾ 1:
          time:         "2020-08-02 16:30:01"
          latitude:     -32.7014738
          longitude:    151.7399089
          iotID:        "3147"
          temperature:  0.604166687
        ▾ txHash:       "0x3fcb939255c12b54c25383fefa3ff2227618163dcdbd5fbb482d7d4962b2f502"
      ▾ 2:
          time:         "2020-08-02 18:38:26"
          latitude:     -33.5069661
          longitude:    151.1898112
          iotID:        "3147"
          temperature:  0.041666668
        ▾ txHash:       "0x3fcb939255c12b54c25383fefa3ff2227618163dcdbd5fbb482d7d4962b2f503"
```


6.2.1 Catch Provenance

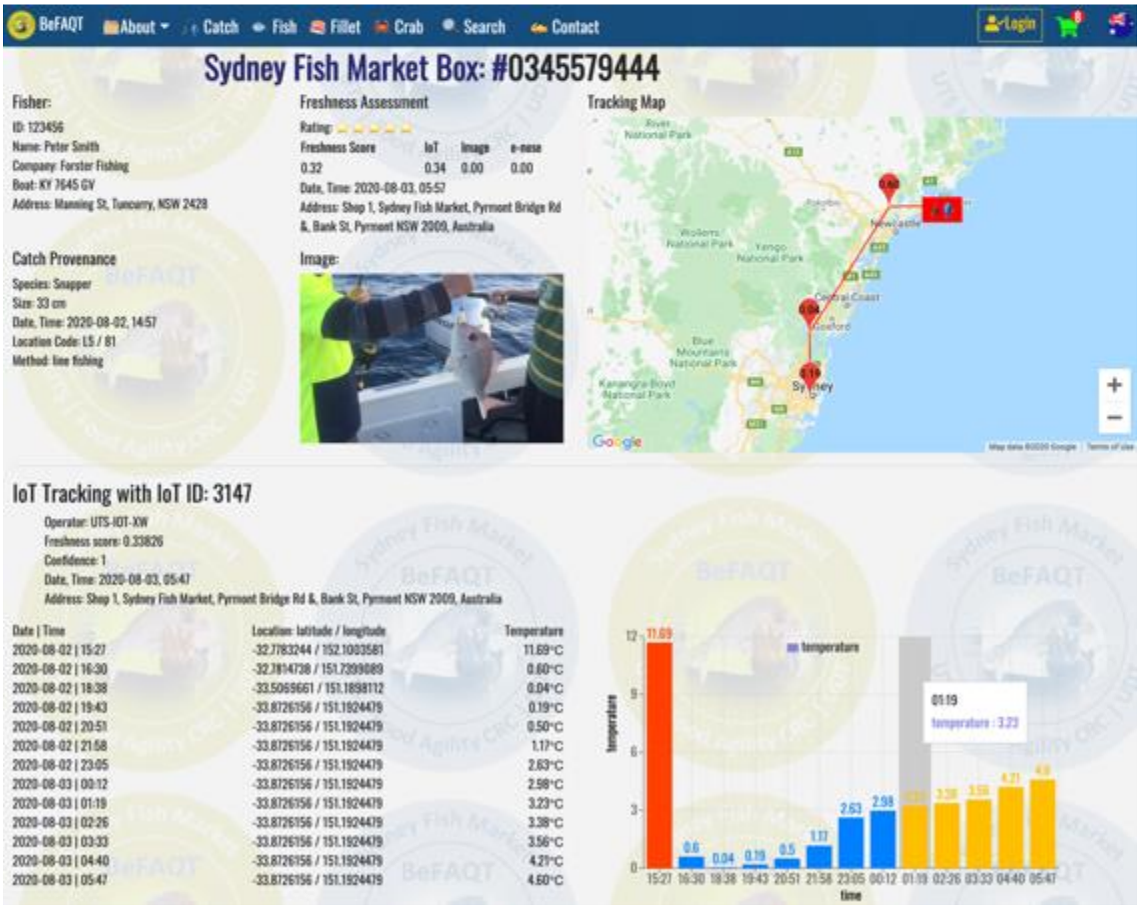
This section records the catch origin obtained from Fisherman App. It contains

- Fisher’s company information
- Catch origin information*

* Note the provenance doesn't show the precise geolocation of the catch. Rather, a NSW DPI catch location code, e.g. L5 / 81, is shown as the location.

6.2.2 Supply Chain Tracking with IoT sensing

Fish supply chain tracking is achieved via IoT and sensors, which record time, location, and temperature throughout the supply chain.

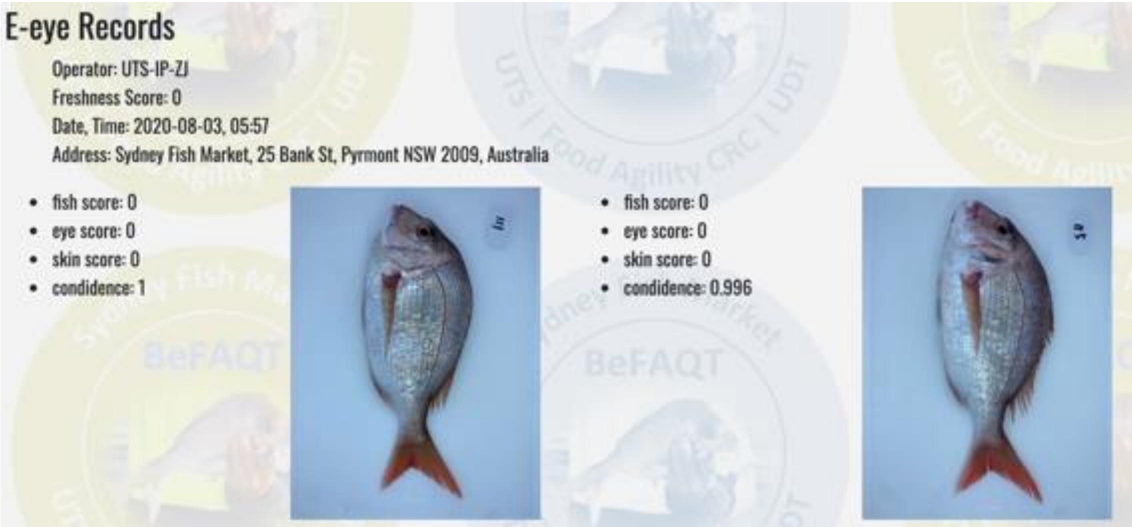


- The Freshness score is assessed from ice days, and confidence level represents the accuracy of the assessment.
- Locations are recorded by IoT devices and the locations are shown in BeFAQT system via Google map.
- The catch origin location is shown as a red rectangle to protect catch privacy

- The temperature is shown as a bar chart, where a temperature below 3°C is shown in blue, above 3°C but below 6°C is shown in orange, while above 6°C is shown in red.

6.2.3 E-eye

E-eye section records fish quality assessment results using image processing technologies. The assessment time and location are also recorded. The original images used for the assessment and raw assessment scores are also shown in this section.



6.2.4 E-nose

E-nose section records fish quality assessment results using e-nose technologies. The assessment time and location are also recorded. The original assessment sensor raw data files are accessible here.

6.2.5 Freshness Assessment

The final freshness assessment score is a weighted average of the assessment scores from: IoT sensing, e-eye, and e-nose. The score is in the range of 0 to 3, where 0 is best (fresh) and 3 is worst (not fresh).

We have converted the freshness score to an easy to understand 5 start rating with the following conversion:

- 0 ≤ score < 0.5: ☆☆☆☆☆
- 0.5 ≤ score < 1.0: ☆☆☆☆
- 1.0 ≤ score: star rating is not shown.

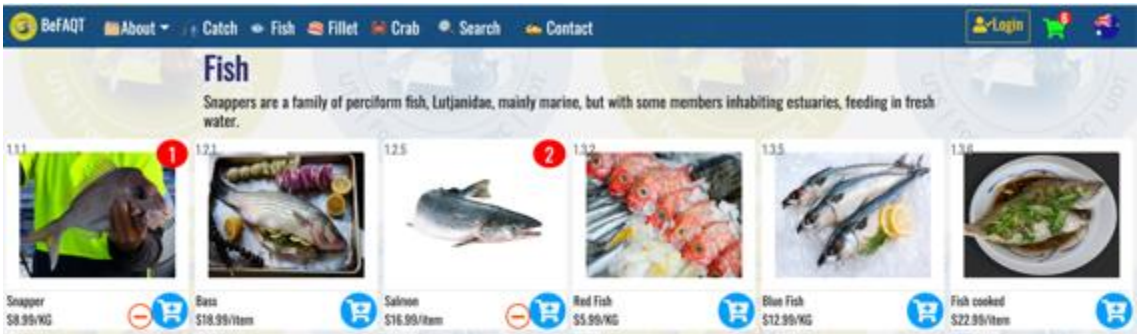
6.3 Online Shopping

Customers can browse seafood products and register to buy in BeFAQT trading platform.

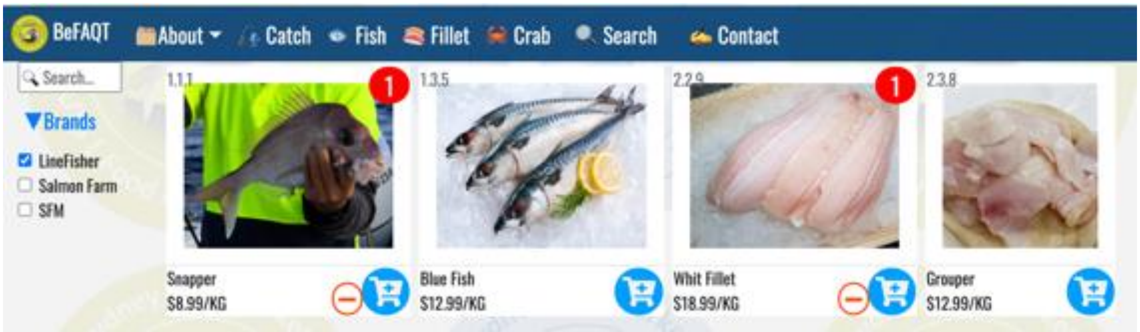
6.3.1 Browsing seafood

The BeFAQT trading platform supports online seafood shopping. Consumers can choose different seafood categories:

and in each category, consumers can choose seafood and put them into the shopping cart



consumers can also search the shop in the Search page. The search can be either text search or search by selecting favourite brands.

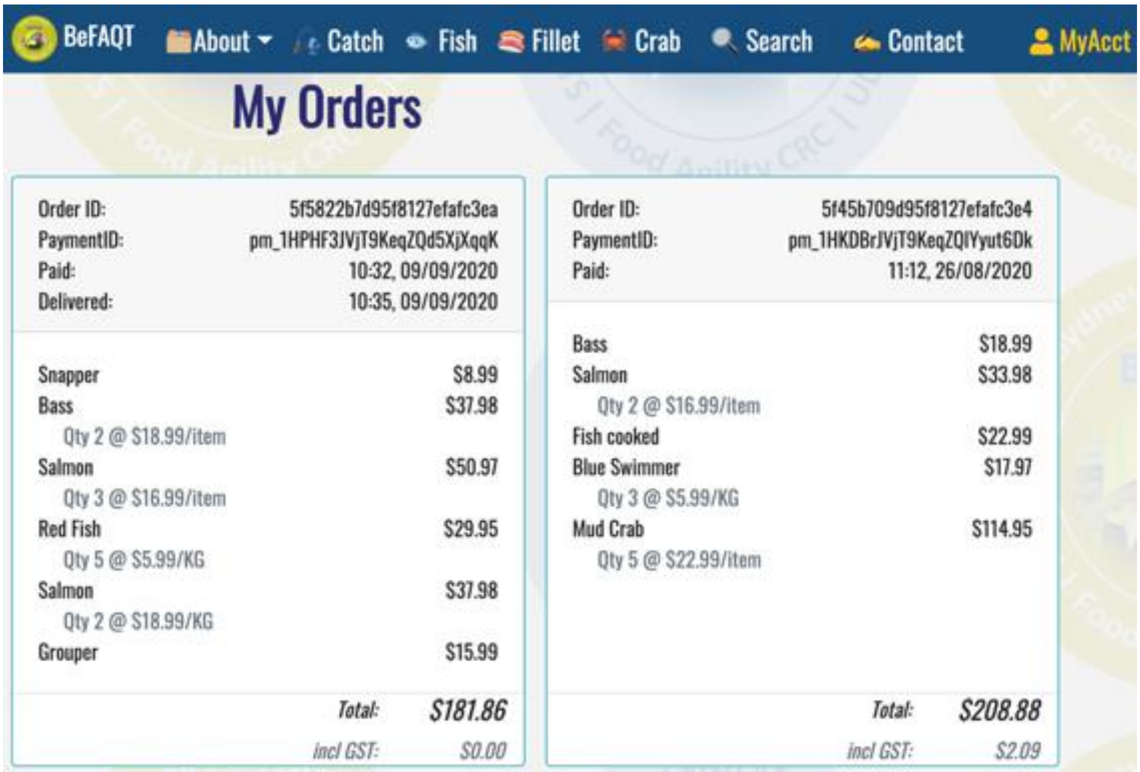


6.3.2 Registered users

Customers can register in BeFAQT trading platform

The registered users are able to manage their own shopping trolley:

A registered user can also check the delivery status of his/her own orders:

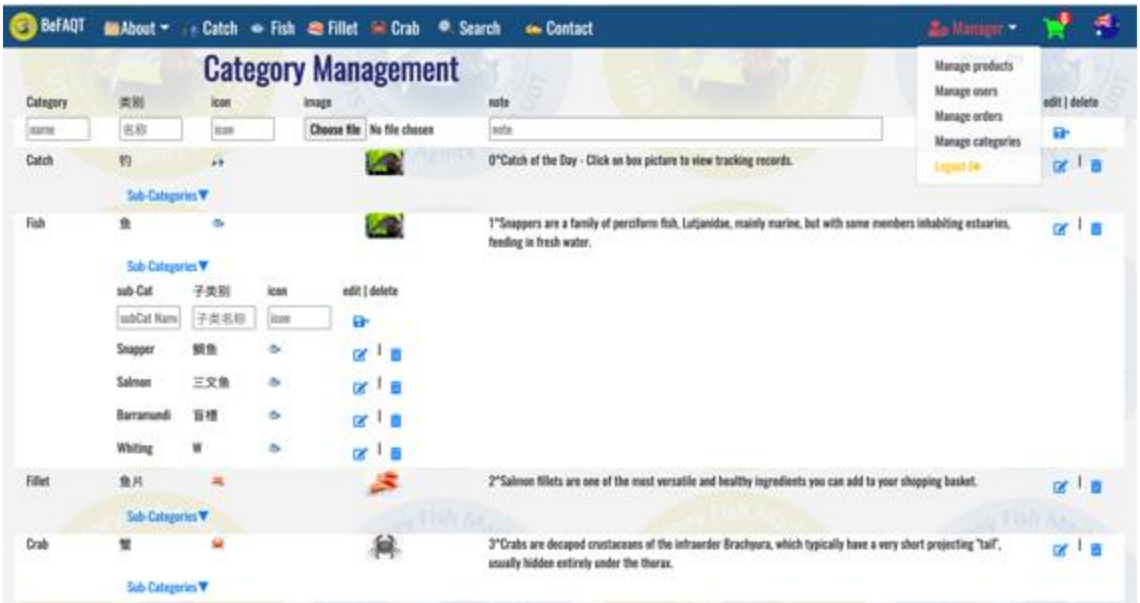


6.4 Online Trading Management

the management functionalities are designed for trading platform owners to manage the products, orders, and users.

6.4.1 Product Management

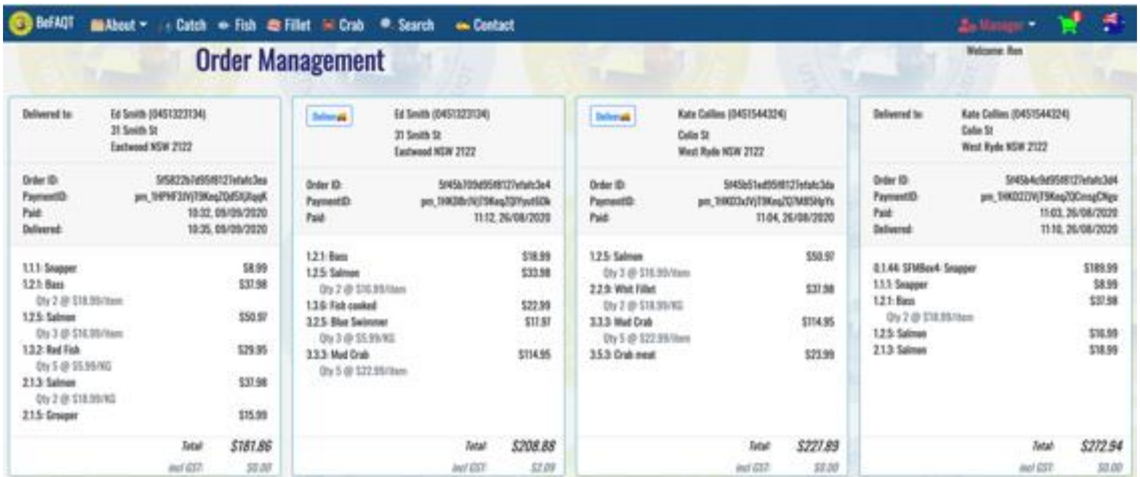
Shop owners can add / update / delete Seafood Categories in the shop by logging in as Admin.



Shop owners can add / update / delete Seafood Products in the shop by logging in as Admin.

6.4.2 Order and customer management

Shop owners can manage product orders. By clicking on the Delivery button, the shop owner can confirm seafood delivery to the customers.



Shop owners can also manage users and their orders.

7 Results

This chapter provides the results of the technology development, including trials with Sydney Fish Market and end users.

BeFAQT won the NSW iAwards 2020 for Business & Industry Solution of the Year!

7.1 Trial Results

[Ren Ping Liu, Xu Wang]

7.1.1 Visit Newcastle Fishermen's Co-Op 22/05/2019

Staff: Ren Ping Liu, Peter Loneragan, Xu Wang

Newcastle Fishermen’s Co-Op - 22/05/2019

- Newcastle Co-Op buys all the fish,
  - some sold locally,
  - some transported to SFM, SFM may recount the fish?
- Two different cool rooms
  - with 2 degree and -30 degree, respectively.
  - No mobile signal in the cool room.
- Fishermen sort fish into SFM fish boxes at Co-Op, weight.

Trip Report | renping.liu@uts.edu.au

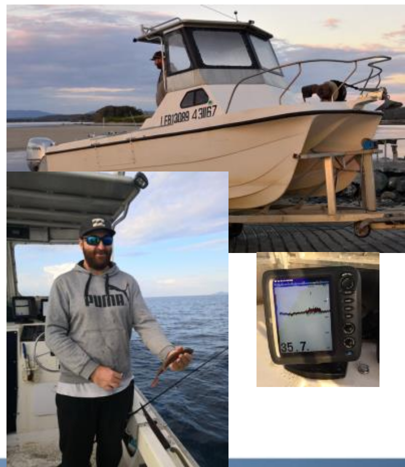
7.1.2 Fishing Trial in Forster, 23/05/2019

UTS Project Staff: Ren Ping Liu, Peter Loneragan, Xu Wang

Fishermen: Jacob Bowland and Mike Jones

Forster Line Fishing - 23/05/2019

- Morning fishing
  - 6:30 am – 12:00 pm, Jacob’s 7-meter boat
  - with Jacob Bowland and Mike Jones
  - with Sonar detector
- Four fishing spots,
  - about 10km off the coast,
  - about 40 meters deep, with reef on the bottom.
  - The reef at the bottom is not suitable for trawlers – leaving a space for small fishers ☺
- Boat roof
  - lights installed (water/salt proof)
  - could attached camera



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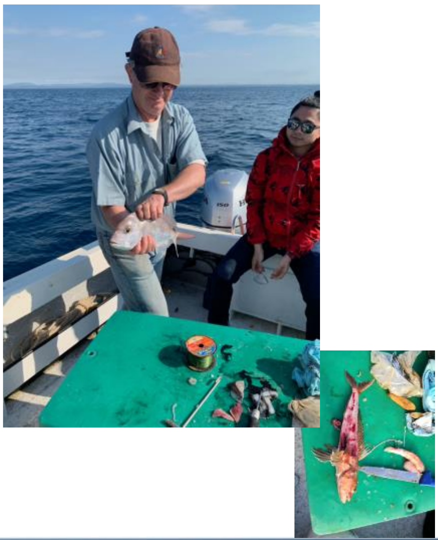
Fishing

- There is one ice slurry on the boat.
  - ➢ It is about 5 times as big as the SFM blue box
- All fish caught throw into the Green ice slurry on board.
  - ➢ Snapper caught could be killed by stabbing the brain - better colour on the fish
  - ➢ Unwanted fish chopped as bait
- Caught about 50 fish with 3 fishing rods,
  - ➢ about 30 fish of legal size kept in ice slurry,
  - ➢ more than half are snappers
  - ➢ about 20+ smaller fish are thrown back



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Process at Co-Op

- Sort Fish (on boat at Co-Op Wharf)
  - ➢ pour ice/water out
  - ➢ Sort fish from Green ice slurry to SFM blue boxes
  - ➢ Snapper in one box, others in another box
- In Co-Op
  - ➢ Measure fish size individually,
  - ➢ further sort into different batches, e.g. snapper medium, snapper small,

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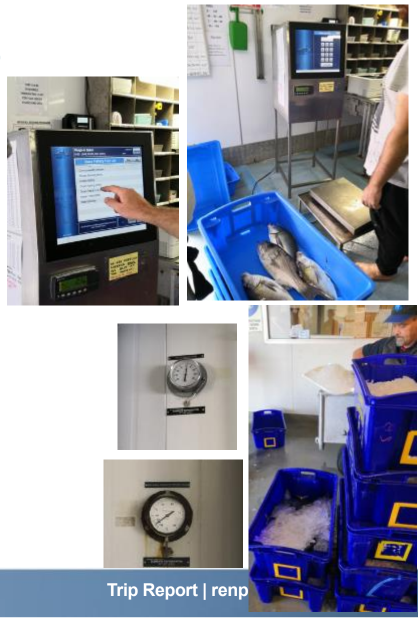
Process at Fishermen's Co-Op

- Weigh and data entry
  - ➢ Input batch species, size, destination - touch screen input
  - ➢ Weigh each batch in a box
  - ➢ print label, put label in the box
- Storage at Co-Op
  - ➢ Add ice into fish boxes, push into cool room
  - ➢ Two different cool rooms with 2ºC and -30ºC, respectively.
  - ➢ No mobile signal in the cool room.
- Co-Op,
  - ➢ some fish sold locally by Co-Op,
  - ➢ some transported to SFM, SFM may recount the fish?
  - ➢ Fisher wait for fish sold in SFM to receive payment



UTS: Trip Report | renp

7.1.3 Field Trial Results

Discussions with Fishers

- Record catch information
  - ➢ Jacob is concerned when he is getting busy, snap a photo on every fish would slow things down
  - ➢ Hanging a camera? Maybe, but the camera might only see his back.
- Suggested catch information at the end of the fishing:
  - ➢ Scan the NFC tag to report location
    - o but rather than precise location, only provide the grid information, N-14, D32
  - ➢ Take a photo in the ice slurry,
    - o but fish are buried in ice, cannot see much
    - o Suggested take a few samples put on top of the Green ice slurry to take photos

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Discussions with Fishers

- Traceability could be a good thing, if
  - ➢ can demonstrate sustainable fishing
  - ➢ can fetch higher price from customers
- Suggested trial for customers' willingness to pay
  - ➢ One box with full tracking information;
  - ➢ the other without.
  - ➢ See if customers are willing to pay higher price for tracking info?

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Mobile coverage on boat

- Mobile network is available and
  - ➢ pretty good at all fishing spots.
- Use of mobile phone
  - ➢ Hands get wet and dirty. The fingerprint sensor and touch screen of smart phone sometimes cannot work properly.
  - ➢ Fishers can answer phone calls
  - ➢ all mobile data good.
  - ➢ Mobile screen can be hard to read, because of strong sunlight and sunglasses.

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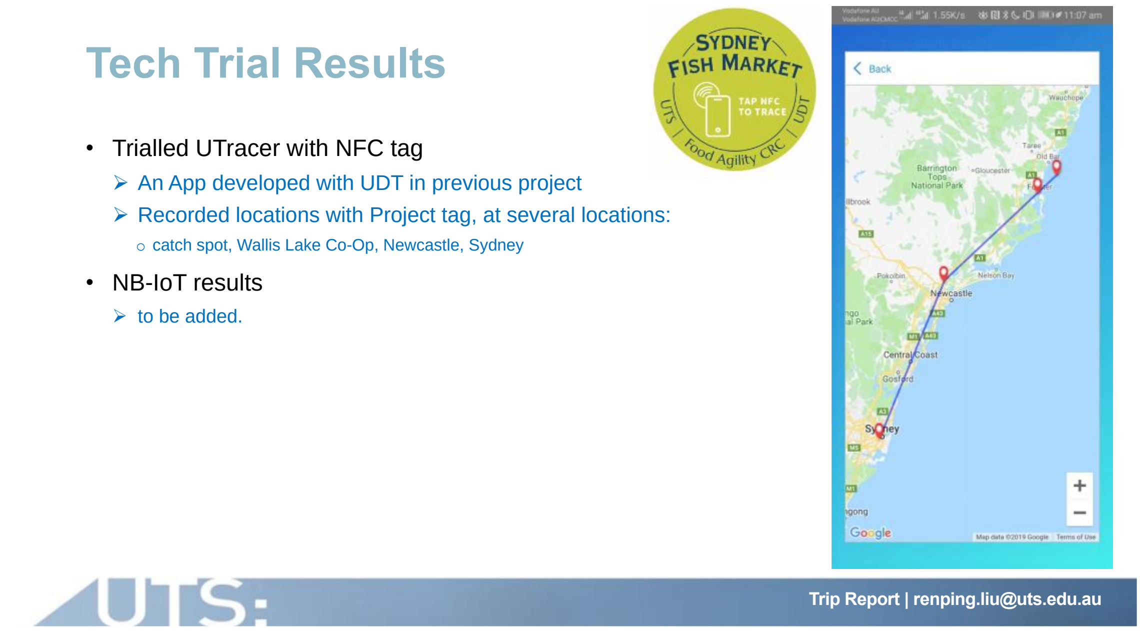


7.1.4 Fish Box Tracking with IoT Trial 03/08/2020

An IoT equipped SFM Fish Box was used in this trial to track the fish supply chain. Supply chain tracking and freshness assessment data are acquired. See section 7.7 for trial results.

7.2 Blockchain Results

The BeFAQT Blockchain is a consortium Blockchain and maintained by four miners. As a result, the Blockchain platform can tolerate maximum one failed miner. The developed Blockchain platform is deployed on the cloud with six servers, as listed in Figure 10. Four of them, i.e., uxchain1, uxchain2, uxchain3 and uxchain4, run the proposed Blockchain consensus protocol and maintain the Blockchain. The RPC server is also a Blockchain node and have all the transactions. The RPC server allows other modules, e.g., the website and the App, to interact with the Blockchain using the HTTP RPC style calls. There is another sever named as API, which provides the HTTP restful APIs to the trading platform and the mobile App. The API server also builds index for the Blockchain data to accelerate the data query.

i-p0w626cexplamz2ejghn rpc	47.91.56.213(Elastic IP Address) 172.20.144.144(Private)	Pay-As-You-Go Created at Jun 7, 2020, 17:58:00	Running
i-p0w626cexplamn87v4mo uxchain1	47.91.42.236(Elastic IP Address) 172.20.144.143(Private)	Pay-As-You-Go Created at Jun 7, 2020, 17:36:00	Running
i-p0wbq9cc6e5pyr2faz0f api	47.74.69.36(Elastic IP Address) 172.20.144.141(Private)	Pay-As-You-Go Created at May 30, 2020, 15:41:00	Running
i-p0w2r5hr959g33o9h5hh uxchain2	47.91.45.181(Elastic IP Address) 172.20.144.140(Private)	Pay-As-You-Go Created at May 22, 2020, 11:21:00	Running
i-p0w148lwoxm7qs5mpvb6 uxchain3	47.91.47.140(Elastic IP Address) 172.20.144.139(Private)	Pay-As-You-Go Created at May 22, 2020, 11:21:00	Running
i-p0w2r5hr959g33o9h5hg uxchain4	47.91.44.118(Elastic IP Address) 172.20.144.138(Private)	Pay-As-You-Go Created at May 22, 2020, 11:21:00	Running

Figure 10 Servers running the Blockchain services

We tested the throughput of the developed BeFAQT Blockchain and the consensus protocol with different length of smart contract playload. According to the result presented in Figure 11, the developed BeFAQT Blockchain can process 1400 transactions per second in the case of L=1, i.e., when the transaction payload is a single letter. The BeFAQT Blockchain can still achieve around 700 transactions per second in when the payload has 50 letters, which is long enough to carry fish quality tracking data.

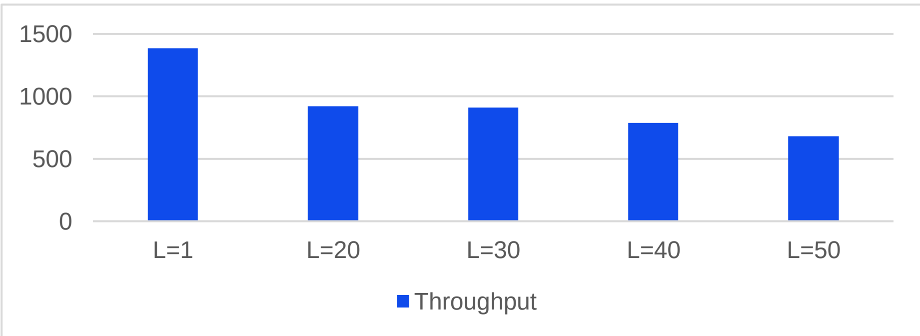


Figure 11 The throughput of the BeFAQT Blockchain with different length of the smart contract payload.

The Blockchain was configured to generate a block in around 12 second to trade off the capacity, delay and storage. The Blockchain data can be viewed via http://exp.befaqt.com/. A screenshot is provided in Figure 12. As shown in the figure, the Blockchain system has generated 393,852 blocks at the time when the screenshot was taken. Blocks were generated on average 12.87 seconds. There were 988 transactions in the Blockchain. The Blockchain is maintained by 4 miners as designed. The two lists under the world state give the blocks and transactions. In the block list, the block number, generated time, proposer and sealer are shown, while the transaction sender, recipient, generated time are listed.

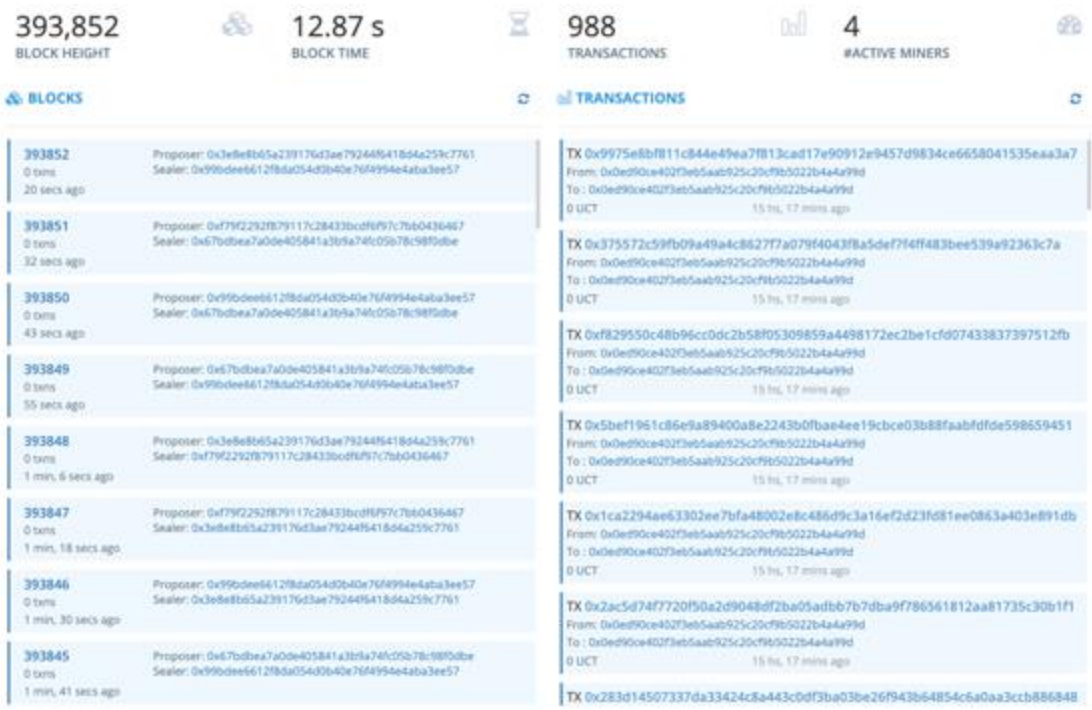
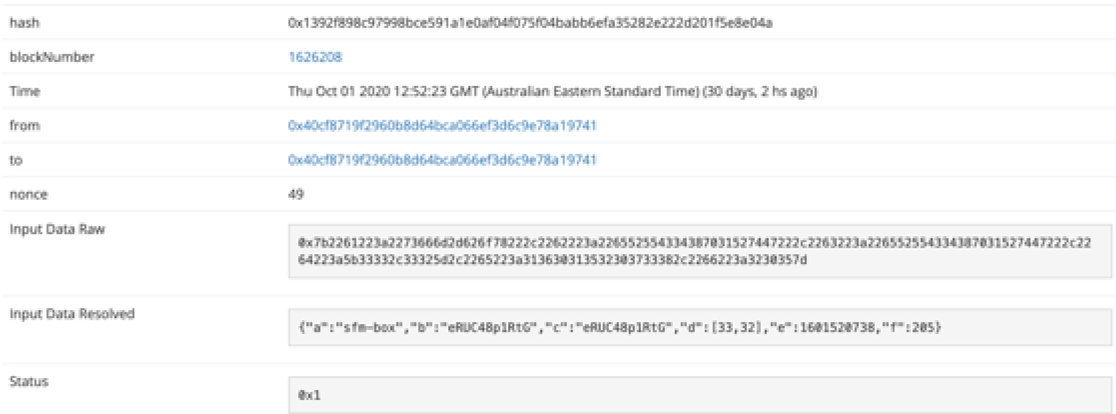


Figure 12 Blockchain explorer.

An example of the transactions is given in Figure 13. The hash is the unique hash value of the transaction and used to locate the transaction. The blockNumber indicates the block containing the transition. The time field is the time when the transaction is accepted by the Blockchain. The from and to fields give the transaction sender and recipient. The nonce is employed to eliminate the replay attack that the same transaction can only be processed once. The following two fields, i.e., input data raw and input data resolved, show the payload of the transaction. The status 1 indicates that this transaction has been accepted by the Blockchain.



hash	0x1392f898c97998bce591a1e0af04f075f04babb6efa35282e222d201f5e8e04a
blockNumber	1626208
Time	Thu Oct 01 2020 12:52:23 GMT (Australian Eastern Standard Time) (30 days, 2 hs ago)
from	0x40cf8719f2960b8d64bca066ef3d6c9e78a19741
to	0x40cf8719f2960b8d64bca066ef3d6c9e78a19741
nonce	49
Input Data Raw	0x7b2261223a2273666d2d626f78222c2262223a22655255433438703152744722c2263223a226552554334387031527447222c2264223a5b33332c33325d2c2265223a313630313532303733382c2266223a3230357d
Input Data Resolved	{"a":"sfm-box","b":"eRUC48p1RtG","c":"eRUC48p1RtG","d":[33,32],"e":1601520738,"f":205}
Status	0x1

Figure 13 A Blockchain transaction example.

7.3 Mobile App Results

The mobile app provides user-friendly functions to both consumers and fishers. The developed mobile app is defaulting the consumer mode and can be switched to fisher mode with a registered fisher login info. The app is connected to the BeFAQT Blockchain via the API server.

7.3.1 Consumer App

With the consumer app, consumers can get the Blockchain-certified fish quality tracking data by simply tapping the smart NFC tags. The main page of the consumer app is shown in Figure 14. There are three tabs, i.e., discover, tracking and profile, on the bottom. The fish quality tracking function is provided in the tracking tab. Consumer can identify fish or fish box in three ways, i.e., scanning QR code, tapping smart NFC tags, and scanning IoT devices. The easiest way is to tap the smart NFC tags where the result is given in Figure 14. As shown in the figure, all fish tracking data, e.g., fish species, dealer, catching time and best before, are clearly given by the app. The quality tracking information are certified by the Blockchain where the corresponding transaction hash value is given on the bottom of the screenshot. The Blockchain certified fish catching photo is also shown on the top left.

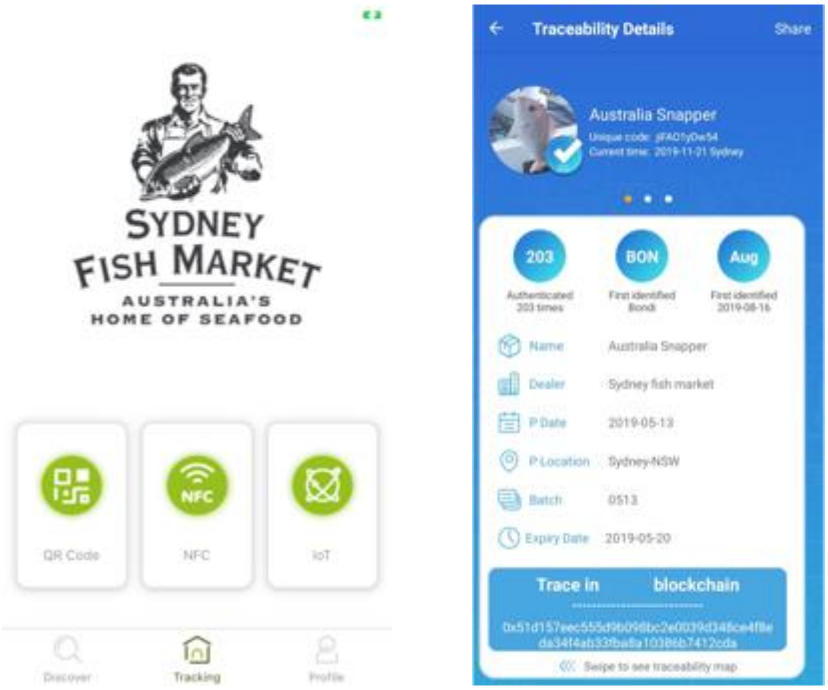


Figure 14 Main page and the quality tracking result of the consumer App

Consumers can swipe for more quality tracking results, as shown in Figure 15. With the list and the map, consumers can verify the fish provenance, stops and inspectors along the supply chain. The red rectangle gives the area where the fish was caught following the NSW DPI guidance.

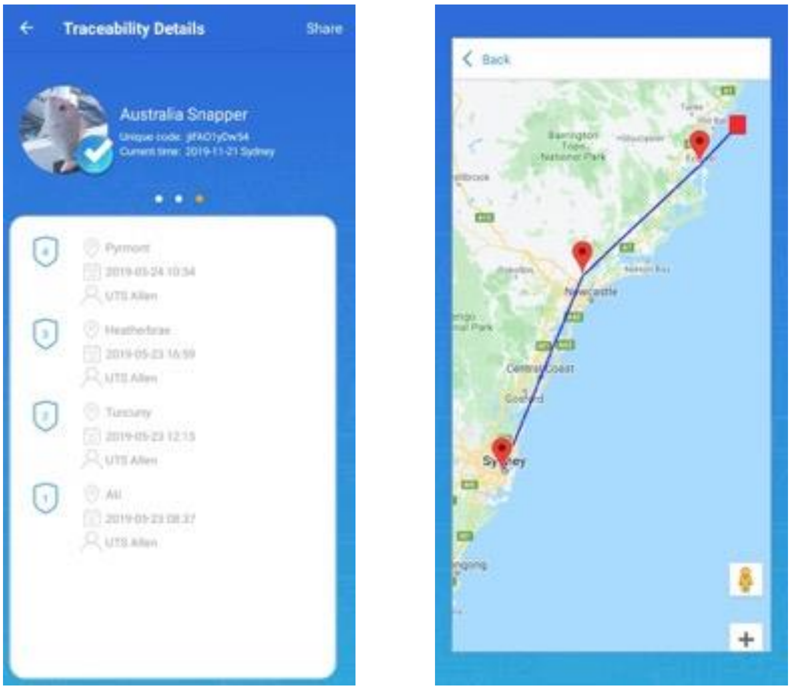


Figure 15 The tracking details and map of the consumer app

7.3.2 Fisher App

With the Fisher App, fisher can take fish photos, record fish provenance, and upload tracking information to the BeFAQT Blockchain. Fishers can switch the app to the fisher mode by login with their verification code. The main page and the profile page of the Fisher App are shown in Figure 16. The main page of the Fisher App provides entrance to take photos for fish catch provenance, boxing fish, check existing fish list and box list, and manage IoT devices. With “Taking Photos”, fishers can take photos of fish for simple catching provenance or sending the photos to E-eye for further processing. With “start boxing”, fishers can link smart NFC tags with fish boxes. With “Scan to Prov”, fishers can scan the fish boxes/tags to retrieve the Blockchain-certified provenance and tracking data. With “Fish List”, fishers can view historical photos of fish and their E-eye results. With “Box List”, fishers can view historical fish boxes. From “IoT management”, fishers can link IoT devices to fish boxes to enable IoT tracking or just scan the IoT devices to stop the IoT devices. The profile page shows the meta data of the fisher, such as name, mobile number, and Co-ops.

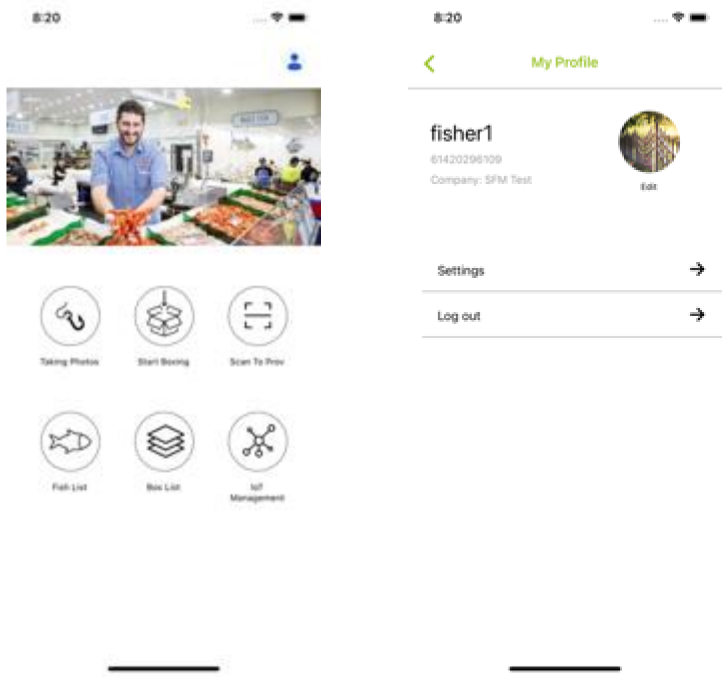


Figure 16 Main page and the profile page of the Fisher App.

During fishing, fisher can use the “taking photos” function to take fish photos, as shown in Figure 17.While the photos are taken, the fishing location and time will be automatically acquired by the Fisher App to eliminate the bias in the paper-based logbooks.

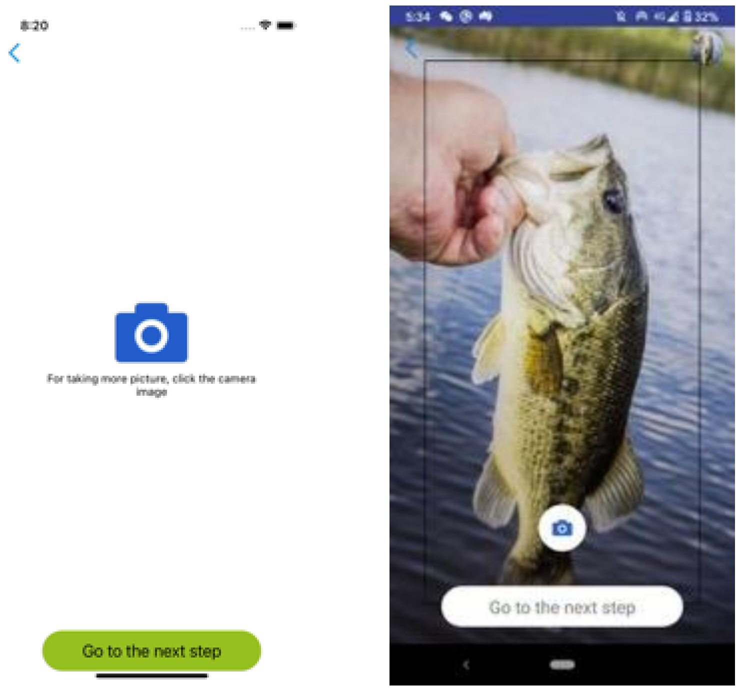


Figure 17 Photo task page and camera page in the Fisher App.

After the photos have been taken, fishers can choose one of three tasks, i.e., fishing provenance, species recognition and sizing, and freshness identification, as shown in Figure 18. In the “fishing provenance”, the photos are just sent the cloud storage and registered in the Blockchain along with the fishing provenance data. In the other two tasks, the URL to the photos are sent to the E-eye module for species recognition and freshness identification. As requested by the E-eye module, fishers need to take multiple photos for better results in image processing tasks. It takes a while to upload photos to the cloud storage and be processed by E-eye algorithms. Fishers can check the E-eye results in the fish list page when the photos have been processed by the E-eye module.

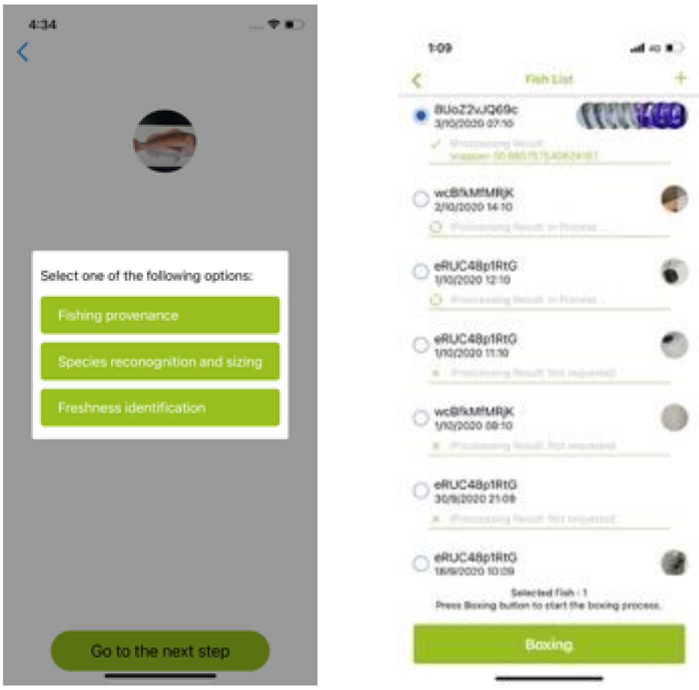


Figure 18 Photo task page and the fish list page in the Fisher App

7.4 IoT Results

The testing of the IoT devices have been carried out in 3 phases:

- Indoor lab testing for basic firmware functionality on the cellular network connectivity and temperature sensor testing without GPS reception.
- Outdoor drive test on cellular network connectivity and GPS reception, with temperature sensor in room temperature.
- Fishing trial:
    - Short sample interval to obtain more data points, with temperature sensor in room temperature
    - Long/practical sample interval to obtain real-life fishing trip, with temperature sensor in the same temperature as the fish box

The results of the above phases are illustrated as follows:

7.4.1 Drive test results

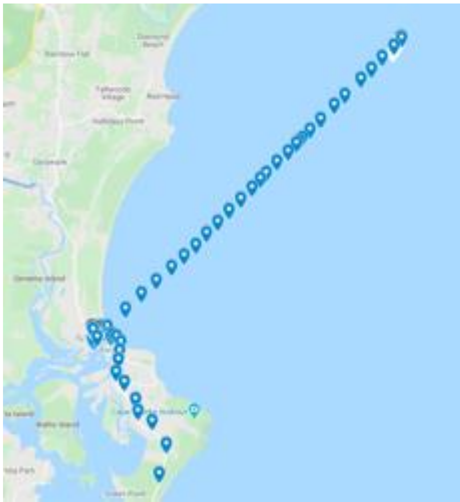
Outdoor drive test results show that our device is able to receive GPS coordinates and send the data via the cellular network to the cloud server.

Figure 7.3.1.1 IoT board v2.0 outdoor drive test results

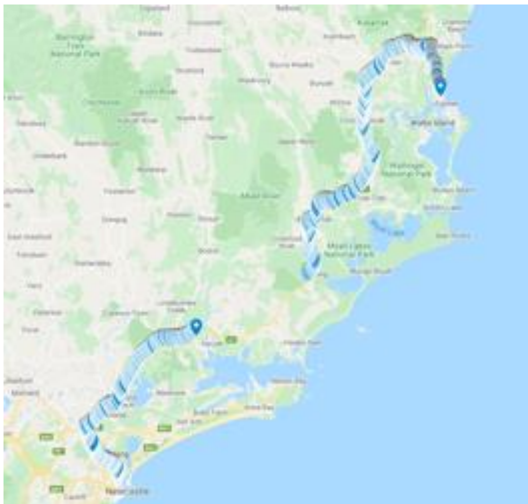
7.4.2 Fishing trial results

We had two fishing trials with fishermen in NSW. The first trial we set a short (5 minutes) sample interval to obtain more data points. We used multiple sims to compare the results between different operator's networks and access technologies. The IoT device was carried by the testing staff along the drive and on-boat fishing. The second trial we set a long (1 hour) sample interval and the IoT device was installed on the fish box. The IoT device captured data along the drive from SFM to the port co-op.

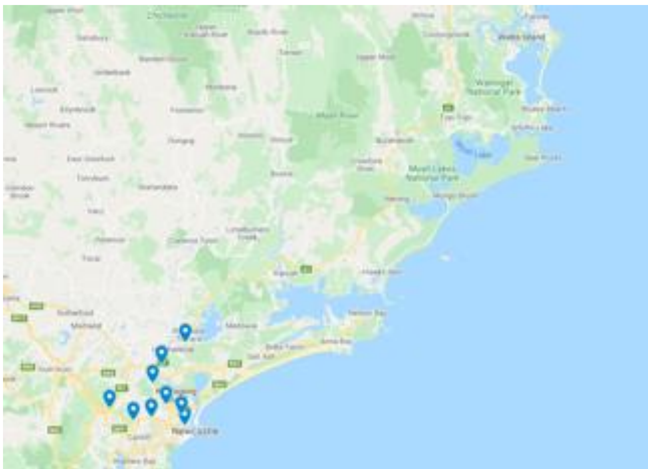
Fishing trial 1 results are shown as follows:



(a)



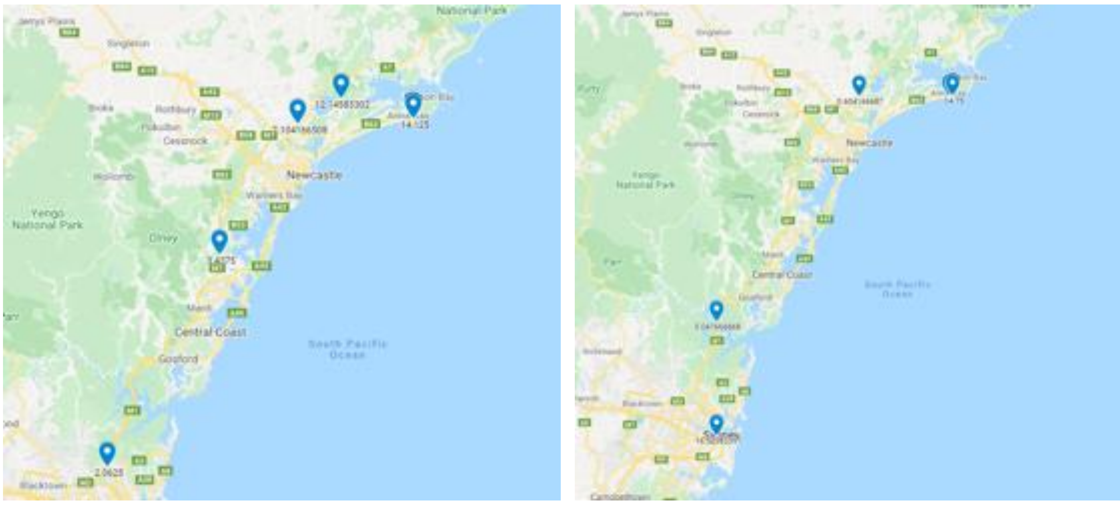
(b)



(c)

Figure 7.3.2.1 Fishing trial tracking results on 23th May 2019

IoT device in room temperature. (a) shows the samples from the port to the fishing location, we can see that the device can transmit data when it is approximately 12-15km offshore with a Telstra sim (b) shows the samples along the drive to the port with a Telstra sim (c) shows samples along the drive to the port with a Vodafone sim. We are able to observe that Telstra network had better coverage along this specific fishing trip.

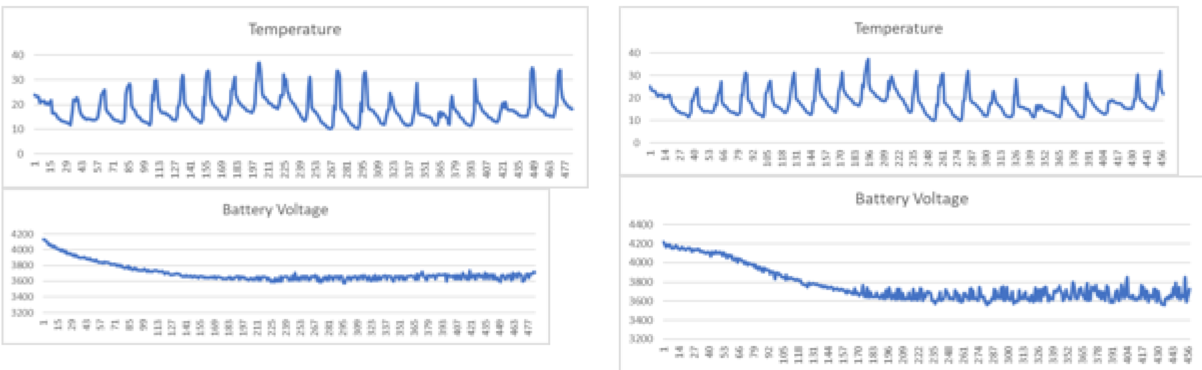


(a) (b)

Figure 7.3.2.2 Fishing trial tracking results on 2nd August 2020

Values on the figures are shown in temperature, with Cat-M and NB-IoT network for (a) and (b). Results show that Cat-M has slightly better coverage than NB-IoT in Telstra networks in the specific area.

7.4.3 Power consumption test results



(a) with 2600mAh battery (b) with 2200mAh battery

Figure 7.3.3.1 power consumption without GPS module

We tested the power consumption of two IoT v1.0 devices connected to two batteries. The battery voltage values are shown in the unit of mV. Sub-figures (a) and (b) show that the device can send 457 and 484 pieces of records with battery 2200 mAh and 2600 mAh Li-ion battery in 21 days with the GPS module turned off.

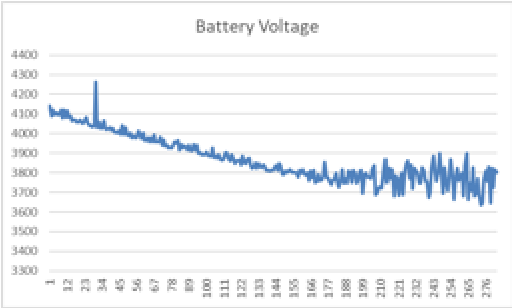


Figure 7.3.3.2 power consumption with GPS with battery 4400mAh

We tested IoT v2.0 power consumption with Cat-M connectivity. Please note the figure shows approximately 50% of the battery life, not a full battery life test. We expect the device can run up to 500 records or 25 days.

7.5 E-eye Results

[Jian Zhang]

7.5.1 Snapper Freshness Identification

A high-quality 40-fish dataset is collected as the benchmark, which includes 8524 images and 181 Fish-Storage-Day (SFD) samples. Trained on this dataset, a new batch of 11 fish are used for real test. So far, test storage dates include day 0, day 3, day 10, day 13, and day 14. In addition to the mobile – iPhone 11 Pro Max, two other mobiles are also used for testing. See Figure 7.4, the overall accuracy tested with iPhone 11 Pro Max is 95.5%. Note this mobile is used for all image data collection. Other two mobiles have slight lower accuracies due to the hardware configuration on camera and different camera drivers. An Android Mate 20 has the lowest accuracy as the Android mobile is much more different from iPhone in terms of configuration and driver. The test results of all three mobiles demonstrate that freshness level 1 has the weakest performances, since the level 1 is the intermediate changing state that the freshness identification model needs either distinguish it from the level 0 or from the level 2.

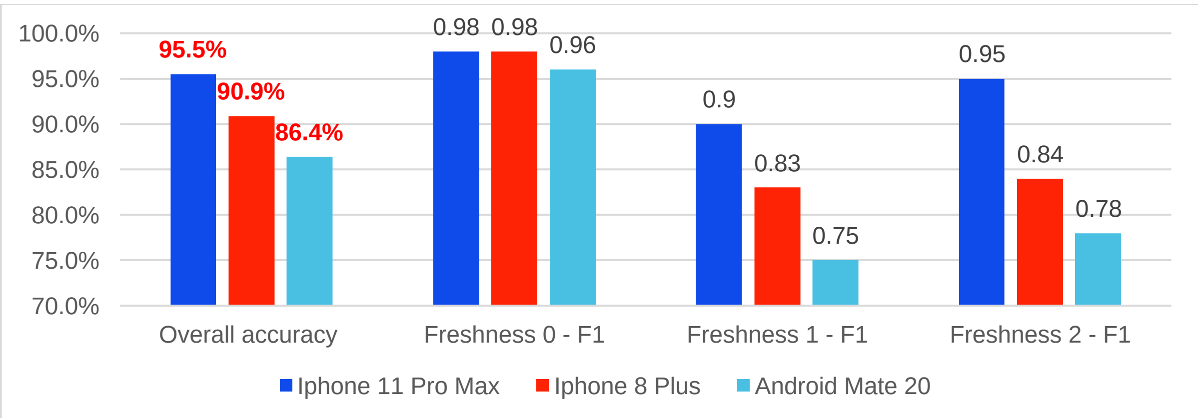


Figure 7.4 Test results of three mobiles for freshness identification

7.5.2 Snapper size measurement

Three mobiles are tested for size measurement to see whether there are any differences between these mobile cameras. The fish that are tested are within the length ranges between 29.3cm and 32.7cm. See Table 7.4 below, there is no obvious difference between different mobile cameras. For two iPhone mobiles, the Mean Absolute Error (MAE) is 0.7cm, and the Standard Deviation (STD) is around 0.56cm. The Android Mate 20 has a slightly higher MAE 0.72cm but lower STD 0.42cm.

Table 7.4 Test results of three mobiles for size measurement

	Iphone 11 Pro Max	Iphone 8 Plus	Android Mate 20
MAE	0.70	0.70	0.72
STD	0.56	0.57	0.42

The position of the mobile camera is a factor that might influence the measurement accuracy. All three mobiles are tested on two heights: 1.5m height and 1m height. See table below, 1m height has a smaller MAE (0.59cm), as closer camera distance is better for the accuracy.

Table 7.5 Test results of two camera heights for size measurement

	1.5m height	1m height
MAE	0.81	0.59
STD	0.46	0.55

7.5.3 Snapper species classification

A high-quality dataset is collected for the benchmark. The dataset includes 1576 snapper images and 2711 non-snapper (more than 20 species) images. A verification test, 80% of the subset data selected for training and 20% of the subset data for testing, is conducted in a random selection for ten times. The overall accuracy is 98%. Tested on a new batch of 11 snappers, the overall accuracy is 100%.

7.5.4 Image processing API system

As all three fish models are designed based on Deep Neural Networks, the calculation load is quite heavy. To achieve a real-time response to the blockchain system, GPU optimisation is conducted to speed up the calculation process. See the Figure 7.5 below, after GPU optimisation, the API response latency for freshness function and size/species function is greatly reduced.

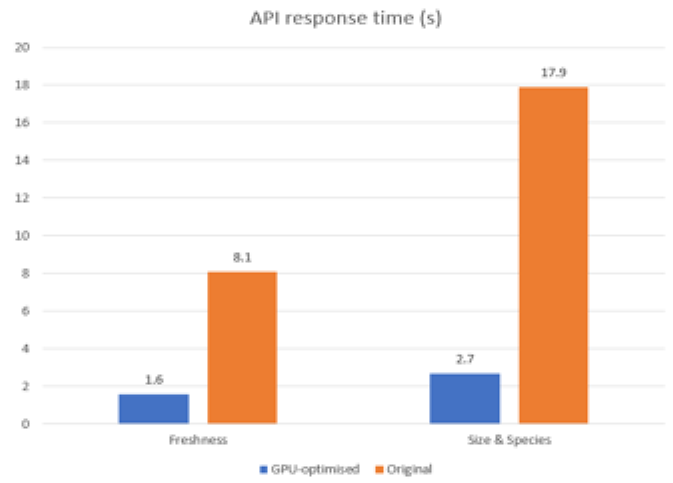


Figure 7.5 Test results of GPU acceleration

7.6 E-nose Results

[Steven Su]

In the first stage of the project, we spent a lot of time and energy on the experiments by placing the fish sample in a fish box filled with ice (i.e., experimental protocol 1). Most of the available data is based on this experimental protocol. So, we summarized the assessment results regarding experimental protocol 1 as follows:

Training set: Accuracy 84.5%

Including: Index 0: 89.8%. Index 1: 81.7%. Index 2: 83.9%

Test Set: Accuracy **73.2%**

Including: Index 0: 86.7%. Index 1: 68.2%. Index 2: 68.4%

As discussed before, the main reason for the relatively low testing accuracy is due to the fact that this fishing box based testing protocol may reduce the sensor sensitivity of the gas sensors due to the lower temperature caused by the ice (see Fig. 5.3.1).

In the late stage, we focused on the headspace bottle based testing protocol, and introduced adjustable thresholds based approach to monitoring the freshness of the fish and predict fish freshness index. We do not have enough expert annotated data to provide a statistics of the classification accuracy of the second experimental protocol based experiment here. The detailed discussion can be seen in subsection 5.3.2.

It should be emphasized, based on our experiences, we found that it was not always the case that the smell of the fish is well correlated with the storage history (i.e., ice days), the image of the fish, and the freshness index recorded by the experts in SFM. One of the reasons as pointed by Eric (SFM) is that a different lure may have a different smell, which can significantly influence the e-nose based fish freshness index prediction. Therefore, the E-nose team prefers to independently provide an original score based solely on fish odor to the BeFAQT system rather than providing a freshness index (Index 0, 1 and 2) based on a classifier.

However, in the presented approach, we also provide an adjustable threshold freshness index prediction method as described in Subsection 5.3.3. We are confident that in the future when our e-nose system is adopted by SFM, the SFM expert will be able to adjust the thresholds to provide a more accurate prediction of the freshness index when more annotated experimental data is available.

7.7 Trading platform Results

[Ren Ping Liu]

The BeFAQT online trading platform (https://www.befaqt.com) was designed to demonstrate the BeFAQT technology development results.

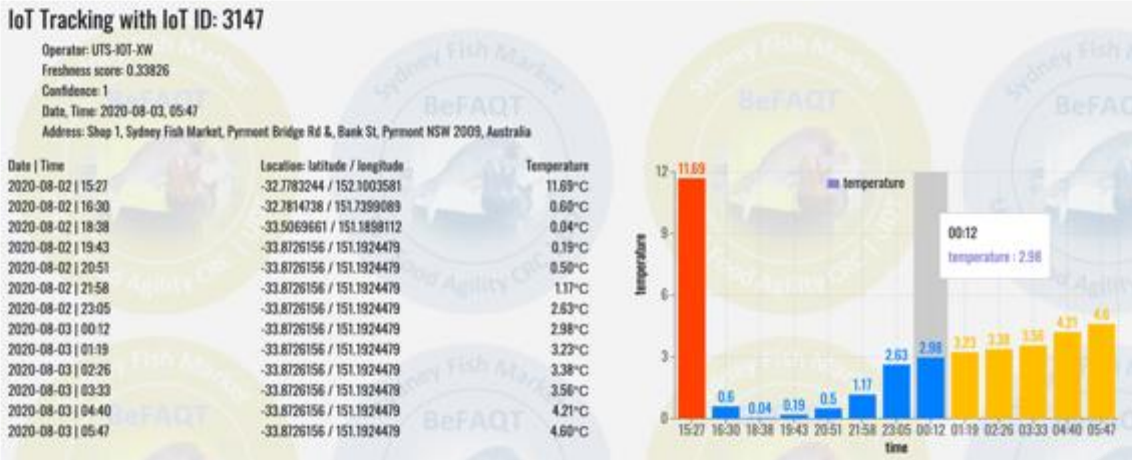
In particular the "Catch of the Day with Tracking Records" page

https://www.befaqt.com/SFMBoxes/byId/0345579444

is used to demonstrate how the fish provenance and quality tracking records can be accessed in future online trading platform.

An IoT equipped SFM Fish Box tracking trial was successfully conducted. The IoT tracking results are demonstrated in BeFAQT platform.

The time, location, and temperature tracking results are shown below:



The returned fish have also been analysed with E-eye and E-nose for freshness assessment:

The catch provenance, supply chain tracking, and freshness assessment are presented in the following summary section, where freshness is summarised from IoT, e-eye, e-nose results based on weighted average. The final freshness score is converted into five-star rating ☆☆☆☆☆.

8 Road Map – BeFAQT Phase 2

This chapter presents the road map for potential BeFAQT Phase 2 development, leading to commercialisation.

8.1 Blockchain Road Map

8.1.1 Blockchain development

The blockchain can be commercialised to support large-scale applications and interaction with other blockchains. The commercialisation includes the following development tasks:

1. Further develop the blockchain consensus protocol to support large-scale commercial applications.
2. Further develop the across chains communication protocols allowing the BeFAQT chain to interact with other blockchain systems.
3. Further develop the smart contract on the blockchain enabling automatic trading, including quality assessment, payment and credit update.
4. Further develop the SFM cryptocurrency to support the automatic trading.
5. Further develop the blockchain explorer and monitor.

Deliverables:

- Production-ready blockchain platform supporting large-scale applications.
- Smart contracts supporting automatic trading.
- Protocols allowing on-chain information exchange among chains

8.1.2 Duration and Budget Estimate

Duration: 18 months

Budget: $100K

8.2 Mobile App Road Map

8.2.1 Mobile App development

The Mobile App can be commercialised to support online trading platform and support real-time supply chain management. The commercialisation includes the following development tasks:

Fisher/Manager App:

1. Integrate with the NSW DPI App.
2. Further develop the real-time supply chain monitoring and management, such as monitor temperature, track boxes and set alarms.
3. Further develop the online trading modules, such as add fish, update fish info and order management

Consumer/buyer App

1. Further develop the online trading module, allowing buyers to check the blockchain-certified quality data, conduct Dutch Auction or other forms of trading. The module includes functions such as top-up, auction, payment management, order management and shipment management.
2. Further develop the buyer management module, such as registration, login and preference setting.

3. Further develop the real-time tracking module to present the location and temperature of shipments.

Deliverables:

- Production-ready mobile apps for fishers and managers, supporting online trading and supply chain management.
- Production-ready mobile app for buyers, supporting online trading and order monitoring.

8.2.2 Duration and Budget Estimate

Duration: 18 months

Budget: $150K

8.3 IoT Road Map

[Ying He]

To fit practical applications, the next step of the IoT development is to find a cost-effective commercial/off-the-shelf product that can track the temperature (and location) during the fishing trip and upload the data when the fishes reach to SFM. We will be working on the system integration and possible optimisation with the off-the-shelf product to our Blockchain platform.

Estimated budget: 6 months 50k

8.4 E-eye Road Map

[Jian Zhang]

8.4.1 E-eye development tasks

The image processing component is a key component to server for the BeFAQT and also support the SFM staff to do their day-by-day jobs if a freshness is concerns over their processing lines and the online auction platform. The commercialisation includes the following development tasks:

Consolidate the lighting box design for the use in real word at Sydney Fish Market (SFM) and easy for SFM staff to use

R/D extension to enhance the freshness assessment by using up-to-date AI model (new deep learning framework) and refine the current image feature extraction to enhance the robustness for freshness identification

R/D extension to enhance the size estimation through advanced AI model (deep learning framework)

R/D extension to enhance the species classification.

R/D extension to fill the gap on different performances when using different brands of mobile phones.

8.4.2 Deliverables

Scale-up to major species (e.g., 10 or more) traded in Sydney Fish Market

A completed image processing backbone platform for fish freshness assessment, size estimation and species classification) including S/W and H/W. This platform will be ready for commercialisations.

8.4.3 Duration and Budget Estimate

Duration: 18 months

Budget: $160K

8.5 E-nose Road Map

[Steven Su]

We will improve the developed E-nose system in both hardware and software design. We have designed a hand hold portable E-nose system, and based on that we will establish models which can estimate the influence of environmental variation to further improve the efficiency and accuracy of the E-nose based freshness assessment.

8.5.1 E-nose development tasks

The major tasks for E-nose commercialization are to complete the design and manufacturing of the handheld E-nose system and develop a fully integrated user interface for fast and reliable freshness index prediction. Accordingly, the following deliverables and budgets are planned in the commercialization phase:

1. Based on the handheld proof-of-concept design, all the designed functions should be integrated into the E-nose user interface, including the integration with BeFAQT system.
2. Functional bench tests should be completed in the lab to verify the final design and prepare the test plan for the third party certified laboratory.
3. Identify the standards which need to be followed to conduct the safety tests (mainly focus on the electrical and EMC tests).
4. If needed, optimise the design according to all the test results, then repeat the stage 2 to 3: 2 Months, Costs included in the above stages.
5. Prepare for the patent application if needed.
6. Cost analysis.
7. Complete the final design, the integration with BeFAQT and document the design.

8.5.2 Duration and Budget Estimate

In summary, the total cost is around 180K AUD and it will take around 18 Months to complete.

8.6 Trading platform Road Map

[Ren Ping Liu]

8.6.1 Trading platform development

The BeFAQT system can be commercialised as a production online trading system. The commercialisation includes the following development tasks:

1. further develop the API to comply with industry Open API standard
2. add online auction facility to support Dutch Auction and support buyers from interstate and overseas
3. further develop user management module to support order dashboard and profile management
4. further develop administrative management module for product inventory, payment, delivery management.
5. develop email and mobile functionalities
6. further develop online payment module to accept multiple payment methods.
7. enhance security with password management and two-factor authentication

At the same time, more trials need to be conducted to test the system with producers, Sydney Fish Market, traders and consumers.

Deliverables:

- Blockchain enabled trading platform with trusted provenance and quality tracking

- Production ready platform with a variety of auction and selling styles, supporting multiple auction / selling floors, multiple languages, currencies, and time zones
- Advanced management and security

8.6.2 Duration and Budget Estimate

Duration: 18 months

Budget: $200K

9 List of Publications

[1] X. Wang, G. Yu, R.P. Liu, J. Zhang, Q. Wu, S. Su, Y. He, Z. Zhang, L. Yu, T. Liu, W. Zhang, P. Loneragan, E. Dutkiewicz, E. Poole, N. Paton, “Blockchain-enabled Fish Provenance and Quality Tracking System,” submitted to IEEE Internet of Things Journal.

[2] Huaxi Huang;Junjie Zhang;Jian Zhang;Jingsong Xu;Qiang Wu, “Low-Rank Pairwise Alignment Bilinear Network For Few-Shot Fine-Grained Image Classification“, IEEE Transactions on Multimedia, accepted, 2020.

[3] T. Liu, W. Zhang, M. Yuwono, M. Zhang, M. Ueland, S. Forbes, W. Su. "A data-driven meat freshness monitoring and evaluation method using rapid centroid estimation and hidden Markov models." Sensors and Actuators B: Chemical 311, 2020: 127868.

[4] Guangsheng Yu, Xuan Zha, Xu Wang, Wei Ni, Kan Yu, J. Andrew Zhang, Ren Ping Liu, "A Unified Analytical model for proof-of-X schemes," Computers & Security,2020

[5] Guangsheng Yu, Xuan Zha, Xu Wang, Wei Ni, Kan Yu, Ping Yu, J. Andrew, Ren Ping Liu, Y. Jay Guo, "Enabling Attribute Revocation for Fine-Grained Access Control in Blockchain-IoT Systems," IEEE Transactions on Engineering Management, Feb. 2020.

[6] Guangsheng Yu, Xu Wang, Kan Yu, Wei Ni, J. Andrew Zhang, Ren Ping Liu, "Survey: Sharding in Blockchains," IEEE Access, 2020

[7] Xu Wang, Ping Yu, Guangsheng Yu, Xuan Zha, Wei Ni, Ren Ping Liu, Y. Jay Guo, "A High-Performance Hybrid Blockchain System for Traceable IoT Applications," International Conference on Network and System Security, December 2019.

[8] Li, L, Liu, Z, Zhang, J & Zhou, X 2019, “Learn Image Object Co-segmentation with Multi-scale Feature Fusion”, 2019 IEEE International Conference on Visual Communications and Image Processing

[9] W. Zhang, T. Liu, L. Ye, M. Ueland, S. Forbes, S. Su. A novel data pre-processing method for odour detection and identification system. Sensors and Actuators A: Physical, 287:113–120, 2019.

[10] T. Liu, W. Zhang, L. Ye, M. Ueland, S. Forbes, S. Su. A novel multi-odour identification by electronic nose using non-parametric modelling-based feature extraction and time-series classification. Sensors and Actuators B: Chemical, 2019.

[11] Huaxi Huang et al. “Compare More Nuanced: Pairwise Alignment Bilinear Network for Few-Shot Fine-Grained Learning,” IEEE International Conference on Multimedia and Expo, ICME 2019, pp.91-96.