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Reduction of Losses and Wastage in Seafoods: The Role of Smart Tools and Biosensors Based on Artificial Intelligence

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Review Article

Abstract

This paper reviews current knowledge on the role of smart tools and biosensors based on artificial intelligence in reducing seafood loss and wastage. This study shows that a variety of biosensors, categorised according to how they function, can be used to measure the quality of seafood. These include optical biosensors, enzyme-based biosensors, immunosensors, microbial biosensors, DNA-based biosensors, electrochemical biosensors, optical biosensors, tissue-based biosensors, and piezoelectric biosensors. Among these biosensors, optical biosensors, electrochemical biosensors, and mechanical biosensors are the most significant. Again, this study report that, for seafood traceability and management, a variety of smart solutions including blockchain technology, quick response (QR) codes, data analytics, digital twins, and radio frequency identification (RFID) tags can be utilised. Catch data, vessel tracking data, and data from the processing plant are some of the different data sources that can be utilised to trace seafood products. Artificial intelligence tools like neural networks, deep learning, machine learning, and others can be used to forecast and improve seafood quality. It is crucial to study the development of biosensors that can properly identify the earliest signs of seafood contamination or rotting.

Keywords: *Blockchain, Quick Response codes, Biosensors, Seafoods, Quality*

Cite this paper (APA)

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1. INTRODUCTION

Seafood is a colloquial and highly diverse food category which comprises of algae, cephalopods, cynobacteria, marine and freshwater finfish species, decapods and bivalves (Cooney et al., 2023). Seafoods are valuable protein source, especially in the case where other animal protein sources are expensive and scarce. Polyunsaturated fatty acids (PUFAs), which are known to influence prostaglandin synthesis and therefore promote wound healing, are among the necessary fatty acids found in seafoods (Kryzhanovskii and Vititnova, 2009; Zhang et al., 2010; Kindong et al., 2017). The demand for marine products (seafoods) is expanding substantially (Power at al., 2023). The increase in demand for seafoods could be attributed to consumers paying special attention towards consumption of foods that are healthy (Ghidini et al., 2019). The nutritional properties of seafoods could also be the cause of this increase in demand (Alamprese and Casiraghi, 2015). Despite the importance and significant increase in demand of seafoods, the resources available for wild catch are becoming scarce (Power at al., 2023).

Seafood losses is considered a serious challenge along the seafood value chain. The phenomenon of nutrient and economic losses along the seafood value chain results in serious wastage and has the tendency of posing health threats to consumers. Millions of people's diets are impacted by the loss of highly nutritious food or comprised, notably in areas where undernutrition and micronutrient deficiencies are widespread (Kruijssen et al., 2020).

As a result of the negative impact of seafood waste on the environment, rising demand for seafoods, coupled with its implication for marine conservation and policy, seafood wastage has gained global attention (Erasmus et al., 2021).

Wastage of seafoods have been attributed to some characteristics they possess. These characteristics that make seafoods prone to wastage includes fishing methods that result in by-catch, presence of digestive enzymes, oxidation as well as microbial spoilage (Ghaly et al., 2010; Love et al., 2015). Seafood loss can be enhanced by processing and storage conditions which can trigger microbial spoilage as well as sanitation (Tesfay and Teferi, 2017; Gyan et al., 2020).

In order to meet the current and future demands of seafoods at the global level, it is important to ensure loss and wastage are cut to minimum barest level. This can be achieved by applying technological innovations that can increase access to food that are cheap all year round without significant loss and wastage. Similarly, the amount of per capita food at the global level should be halved by 2030 at both the consumer and retail levels (Kruijssen et al., 2020). Also, along the production and supply chain levels, of which post-harvest is not an exemption, losses should be halved (United Nations, 2014).

Several smart tools and biosensors based on artificial intelligence have been applied in the seafood industry to cut down losses and wastage. These includes quick response (QR) codes, block chain technology, digital twin, data analytics, radio frequency identification (RFID) tags and FishNChip biosensor.

This article is aimed at providing an overview of smart tools and biosensors based on artificial intelligence that can be used to prevent losses and wastage of seafoods. This study is significant as it will serve as the basis and an established framework for further research work in the use of biosensors and smart tools based on artificial intelligence to reduce seafood loss and waste. In addition, creation of database on these possible biosensors and smart tools in reduction of seafood losses and wastage has the tendency to cause a notable improvement in the quality and quantity of seafoods produced.

2. METHODOLOGY

2.1 Literature search

For the purpose of achieving the objectives of this study, studies that had previously reported on application of various smart tools and biosensors based on artificial intelligence in monitoring seafood quality and food in general were searched and used. Papers published in only English were included in this study. No specific duration or date of publication was considered. Data bases such as IEEE, CAB abstracts, Ajol and Scopus were considered. Also, articles published in Elsevier, Taylor and Francis, and Wiley were considered.

2.2 Search strings

In order to identify papers relevant to this study several words and their combinations were used to search the above-mentioned databases. These words include ''internet of things'', wastage, seafood, losses, artificial intelligence, biosensor, deep, machine, learning, quick response scan, radio, frequency, identification, block, chain, technology, quality, supply, chain, electronic, monitoring, systems, neural, network, digital, twin.

3. BIOSENSORS FOR SEAFOOD QUALITY MONITORING

A biosensor is a quantitative analytical instrumentation approach that combines a physico-chemical transducer with a biologically derived sensing element (Surya et al., 2019). They are analytical tools that transform a biological response into an electrical signal (Mehrotra, 2016). Biosensors can measure chemical or biological reactions and turn the result into an electrical output (Bhalla et al., 2016; Franceschelli et al., 2021). By detecting minute changes and converting them into electric signals using signal conversion components like electrodes and optical devices, biosensors can measure specific target compounds quickly and easily (Grieshaber et al., 2008; Endo and Wu, 2019). Output signal, analyte, application, power source and sensor material are the different categories of sensors (Naresh & Lee, 2021; Saeed et al., 2022). Controlling the production environment and creating intelligent food packaging could both benefit from the use of biosensors (Wang et al., 2022).

Different types of biosensors are used in the monitoring of seafood quality. They are classified based on their working principles. These include optical biosensors, enzyme-based biosensors, immunosensors, microbial biosensors and DNA-based biosensors. Others include electrochemical biosensors, optical biosensors, tissue-based biosensors and piezoelectric biosensors. Biosensors with optical characteristics, mechanical biosensors, and electrochemical biosensors are the most significant types of biosensors (Ali et al., 2020). It is said that electrochemical biosensors are highly sensitive, simple to use, and fast to detect (Qiao et al., 2020). Electrochemical biosensors are however known for their precision, direct change detection based on the interaction of the sensor with the sample, low cost, and downsizing potential (Ali et al., 2020). Mechanical biosensors typically benefit from properties that scale well as physical size is decreased (Arlett et al., 2011). According to the chemical interactions between the sensor and the analyte, mechanical biosensors are often divided into four major categories: affinity-based assays, fingerprint assays, separation-based assays, and spectrometric assays (Arlett et al., 2011). When a biorecognition element interacts with an analyte, optical biosensors monitor for changes in phase, polarization, or frequency in the light field (Borisov and Wolfbeis, 2008; Purohit et al., 2020). This type of biosensors can be categorized into fluorescence, absorption and luminescence-based biosensors depending on the transduction mechanism used (Wang et al., 2018).

In addition to this, labelled versus label-free biosensors can be distinguished based on the purposes for which labels are used (Sadik et al., 2009). According to Purohit et al. (2020), labelled biosensors use a reporter or label to detect analytes such as enzymes (e.g., catalase, alkaline phosphatase, and horseradish peroxidase), electro-active substances, or fluorescent molecules. However, label-free approaches rely on BREs recognizing the target, and their straightforward design encourages the creation of portable devices (Purohit et al., 2020).

Some studies have been conducted with respect to the application of biosensors in seafood quality monitoring. Table 1 is a summary of studies reporting on the use of biosensors in seafood quality monitoring.

Table 1. Summary of studies on application of biosensors in monitoring of seafood quality.

Sensor	*Application*	*Findings*	*Reference*
Enzyme-based TMA (trimethylamine) biosensor	Analysing freshness of fish with extractions of horse-mackerel	◆ Due to the breakdown and decomposition of fish samples at 25 °C, sensor output increased with time.	Mitsubayashi et al. (2004)
Disposable biogenic amine biosensors	Determination of histamine in fish samples	◆ For histamine, diamine oxidase biosensors produced a linear concentration range of 9.9 × 10−6 to 1.1 × 10−3 M, while a monoamine oxidase-based sensor produced a linear concentration range of 5.6 × 10−5 to 1.1 × 10−3 M. ◆ Histamine levels and their recoveries determined in fish ranged from 100.0% to 104.6%.	Koçoğlu et al. (2020)
Amperometric biosensor	Determination of histamine in fish samples	◆ Excellent reproductibility and high ability was exhibited by the developed sensor ◆ Low limit of detection as well as high sensitivity was exhibited by the developed biosensor. ◆ Results obtained from the use of the biosensor to determine content of histamine was similar to that of ELISA (the reference method) for greater weever, mackerel and sardines.	Pérez et al. (2013)
Amperometric Enzyme Sensor	Redox-Mediated Determination of Histamine	◆ This selective sensor was effectively used to analyze spiked tuna and mackerel extracts, with recovery values of 99–100%. ◆ It had a low limit of detection (0.97 mg L^{-1}) and accurate and exact results. ◆ The sensor demonstrates good stability, retaining 87.7% of its initial signal after 35 days.	Torre et al. 2019
Amperometric Biosensor	Histamine Detection	◆ The biosensor exhibits great sensitivity (0.0631 A/M), a small detection limit (2.54 10'8 M), and a wide linear domain (0.1 to 300 M). ◆ The quantification of histamine in freshwater fish has been used to test the applicability of this enzyme sensor in natural complex samples and the analytical parameters. ◆ All freshwater fish samples tested showed excellent correlation between the results obtained with the new biosensor and those obtained with the traditional approach.	Apetrei and Apetrei (2016)
A Screen-Printed Disposable Biosensor	Selective Determination of Putrescine	◆ The determination of Put in anchovies and zucchini was successfully done using the biosensor.	Henao-Escobar et al. 2013
Electrochemical Biosensor with Nano-Interface for Xanthine Sensing-A Novel Approach	Estimation of Fish Freshness	◆ The biosensor displayed a peak response in less than 2 seconds and was impervious to ascorbic acid, urea, and sucrose interferences. ◆ It was discovered that the Michaelis-Menten constant (Km) is 1.3 nM. ◆ The limit of quantification is determined to be 8.3 pM and the limit of detection to be 2.5 pM.	Thandavan et al. 2013
Amperometric Biosensor	Detection of Fish Freshness	◆ After seven days, the fish showed very rapid degradation, and it was shown that the level of hypoxanthine increased with storage time.	Dolmacı et al. 2012
Amperometric Xanthine Biosensor	Detect xanthine in fish meat	◆ The biosensor showed optimal performance in 5 s at pH 7.0, 35 °C, and linearity for xanthine from 0.8 M to 40 M with a 0.8 M detection limit (S/E = 3). ◆ For xanthine oxidase, the Michaelis Menten constant (Km) was 13.51 M and the Imax value was 0.071 A. ◆ When kept at 4 °C, the biosensor, which detected xanthine in fish meat, lost 40% of its initial activity after 200 uses over a period of 100 days.	Devi et al. 2011

Sensor	Application	Findings	Reference
Xanthine Biosensor using Polymeric Mediator/MWCNT Nanocomposite Layer	Fish Freshness Detection	◆ The addition of MWCNT to the polymeric mediator film, which was crucial to the biosensor's efficacy, caused the biosensor to respond well to xanthine. ◆ The biosensor demonstrated strong storage stability and a decent level of anti-interference.	Dervisevic et al. 2015
Enzyme-based amperometric biosensor	Detect histamine and histamine-producing bacteria in tuna.	◆ The recovery of histamine from cultures and tuna samples was extremely high (mean bias 12.69 to 1.63%, with root-mean-square error 12%), and HPLC and biosensor techniques produced results that were comparable in the range from zero to 432 g/g (correlation coefficient, R^2 = 0.990). ◆ These findings unequivocally demonstrate that fresh tuna is frequently tainted with potent HPB. ◆ The operators of food businesses might use the histamine biosensor as a screening tool to find them and decide whether or not their process controls are sufficient.	Trevisani et al. 2019
Enzyme-based histamine biosensor	Changes in histamine and volatile amines of threadfin bream, mackerel, emperor bream, sardine, trevally and barracuda	◆ Neither the sensory changes nor the presence of volatile amines was correlated with the histamine concentration. ◆ It was discovered that the histamine production in trevally was quite high and comparable to that of mackerel. ◆ Prior to becoming organoleptically unsatisfactory, mackerel, sardine, and trevally may induce histamine poisoning issues.	Shakila et al. (2003)
DNA based biosensor	This study employed using existing seafood allergen detection method associated with DNA-based biosensor in comparisons to protein based and aptamer-based sensors	◆ Among them, the DNA-based detection approach is an indirect analysis that uses the allergen's gene as the object of detection and is distinguished by its high sensitivity and good stability.	Li et al. (2022).
	In order to identify Vibrio vulnificus in aquatic products, this study used DNA-based approaches.	◆ The proposed biosensor exhibited an excellent capacity to detect marine products contaminated with *V. vulnificus*.	Fan et al. (2021).
Optical biosensors	Detection of paralytic shellfish poisoning	◆ The decision limit (CCα) was 100 µg/kg, with the detection capability (CCβ) found to be ≤200 µg/kg. Repeatability and reproducibility were assessed at 200, 400, and 800 µg/kg and showed relative standard deviations of 8.3, 3.8, and 5.4 % and 7.8, 8.3, and 3.7 % for both parameters at each level, respectively.	Campbellet al. (2013).
Piezoelectric Biosensor	Detection of marine derived pathogenic bacteria	◆ By continuously monitoring frequency shifts, the sensor system was able to identify *V. vulnificus* in a dose-dependent way and within five minutes, bacterial cells were detected.	Hong & Jeong. (2014)
Immunusensor	Detecting tetrodotoxins in shellfish and European fish	◆ The immunosensor enabled the determination of TTXs at levels as low as 0.07 mg TTX equiv. kg−1 tissue, thus, well below the Japanese value of 2 mg TTX equiv. kg−1 tissue used as a criterion to consider puffer fish safe for consumption.	Reverté, et al. (2017)

4. SMART TOOLS FOR SEAFOOD TRACEABILITY AND MANAGEMENT

The safety of food is an important issue that affects health (Sahin et al., 2023). This is because approximately 420,000 people die annually from consuming contaminated food, with additional 600 million becoming ill (World Health Organization, 2019). There is therefore the need to consume foods that are healthy. Investigating the safety and quality of food products can help with this. For food supply chain management (SCM) systems, particularly for seafoods and live items, traceability is a crucial safety measure.

According to the Codex Alimentarius Commission (CAC, 2016), traceability is defined as the ability to follow the movement of a food through specified stage(s) of production, processing and distribution.

Traceability in the context of seafood is the tool that allow consumers, processors and seafood stakeholders to monitor the movement of seafoods along the value change; that is production, processing as well as distribution (Dopico et al., 2016).

For the most part, traceability has been viewed as a technological prerequisite for companies to comply with laws governing food safety, food recalls, and country-of-origin labelling (Tamm et al., 2016). In order to ensure the quality of seafoods are high, sustainable and safe, smart tools can be used to track seafood products from along the value chain from harvesting to sales or consumption point.

Traceability is important because it has been used globally as a tool to prevent and manage risk involved in the supply of food that is unsafe along the supply chain. It also aids in the recall or withdrawal of unsafe seafoods by regulators and manufacturers (Rao et al., 2022). Also, along the supply chain of the food system, traceability is essential as it helps in identification of sources of contamination and their routes (McMillin et al., 2012).

Different types of smart tools such as block chain technology, quick response (QR) codes, data analytics, digital twin and radio frequency identification (RFID) tags are used for traceability and management of seafoods. In this section, the characteristics of these useful smart tools and their application in seafood industry for traceability and management purposes are discussed.

4.1 Radio Frequency Identification (RFID) tags

Radio frequency identification (RFID) tags are small electronic devices that can be attached to seafood products to track their movement and location throughout the supply chain. RFID tags are also referred to as a transponder (Kumar et al., 2009). RFID is a catchall name for systems that identify objects using radio frequency signals. RFID offers extra space to store data and uses radio waves to automatically identify items in a flexible way. However, a variety of problems with regard to time and money demands as well as possibilities for fraud present challenges for RFID (Bilal and Martin, 2014; Mol 2014; Vo et al., 2020). With RFID, an object can be identified from a distance without a line of sight. RFID tags can be read by scanners and can provide real-time information about the product's origin, processing, and distribution. A tag, a reader, which collects data; and database and information management software are the three major components of a typical RFID model (Aydin & Dalkilic, 2018; Sedghy, 2019). Its technology is based on wireless communication, specifically radio frequency waves, between an interrogator and a tag attached to an object (Bibi et al., 2017; Aydin, 2019).

RFID sensors can be used to monitor the freshness of seafoods and to a larger extent its quality by observing the changes in the dielectric properties of each seafood (Potyrailo et al., 2012). This technology has been applied in the seafood industry with success over the past years. Several studies have been conducted with respect to Systems for Traceability Based on RFID (Hsu et al., 2008; Abad et al., 2009; Yan et al., 2012; Treber et al., 2013; Kokkinos et al., 2018; Zhang et al., 2019; Coronado Mondragon et al., 2021).

An RFID-enabled SCM tracking system for live fish had been suggested by Hsu et al. (2008). In this study, the data required for processing live fish was gathered, and ideas for the entire management system architecture, geared toward SME solutions, were developed. Each live fish was given an RFID tag in this manner to track its movement in the restaurants that sell live fish and logistic centers, as well as to give customers identity information.

Abad et al. (2009) created a real-time RFID smart tag for applications including the tracking and monitoring of cold-chain food. This process involved the use of a reader/writer and a smart tag, which was applied to the merchandise. These tags included an antenna for RFID tag transmission, integrated lighting, temperature and humidity sensors, a memory to store product data, and other components. The traceability information gathered by the sensors and stored in the memory chip. The investigation then used a wireless reader with a mobility option to read the food chain data that had been gathered from a distance of 10 cm. With the help of this technique, it was possible to automatically track records, read product data, and check the cold chain's temperature online. Furthermore, this approach eliminates the need to open the polystyrene containers holding the fish and smart tags, allowing the completely automated reader to read many tags at once. Additionally, the system makes sure that the temperature for frozen goods is kept below 0 ºC utilizing temperature sensors. Additionally, the system has humidity sensors, making it sensitive to changes in humidity around the storage environment.

Two separate examples of farmed fish tracking systems appropriate for small- and medium-sized enterprises (SMEs) were presented by Treber et al. (2011). In the first, a small business implemented an electronic RFID-enabled system in place of a manual data collection approach. This project produced an end-to-end SCM solution for farm fish that is beneficial to selling organizations and individual consumers. The second solution involved managing a portion of the automated fish packing process that was improved by RFID technology and branded with a barcode. In this instance, the goal was to transition from a manual data gathering approach to an RFID-enabled data collection method so that traceability could be extended to fish farms for breeding and on-growing.

Using IoT, RFID, and WSN, Kokkinos et al. (2018) created an aquatic product traceability solution. The system included an internet platform that could be accessed from mobile, intelligent devices like an RFID reader. To monitor and verify the security of aquatic products from their catch to the consumer's table, a system was developed. Through the use of the RFID system and the Arduino platform, several wireless sensors were integrated. For sustainable fisheries, the circumstances of the fisheries, the variety of capturing sites, and the quality of the fish products were all maintained. Also, routines relevant to the Greek sea were offered utilizing both traditional and contemporary Artificial Intelligence (AI) techniques, depending on the circumstances and quality assessment.

A smart traceability platform built on the Hazard Analysis and Critical Control Points (HACCP) standards was proposed by Zhang et al. in 2019. With this technique, quality control modelling and wireless facility monitoring were combined to improve fish quality as well as the security and openness of waterless fish transport. Therefore, to provide customers with traceability functions for any tracking-related inquiry, a QR code and the electronic product code (EPC) of the RFID tag were integrated. In this method, buyers were instantly given answers to questions about safe transportation, from aquaculture to markets. Sturgeon delivery trials in particular were evaluated and investigated.

For the fishery sector, Mondragon (2020) suggested a two-layer architectural approach. The surrounding energy consumption of a sensor network was modelled in this study using a sensor layer based on WSN theory. Data were gathered in the first phase from sensors used to monitor the water. Time series/scatter diagrams were used to examine the acquired data. Thus, the patterns and trends of snow crab catch settings were discovered. Finally, this study provided a set of resources for upcoming fisheries researchers to put together this strategy as a monitoring tool for SCM in fisheries leveraging on IoT solutions and RFID technology.

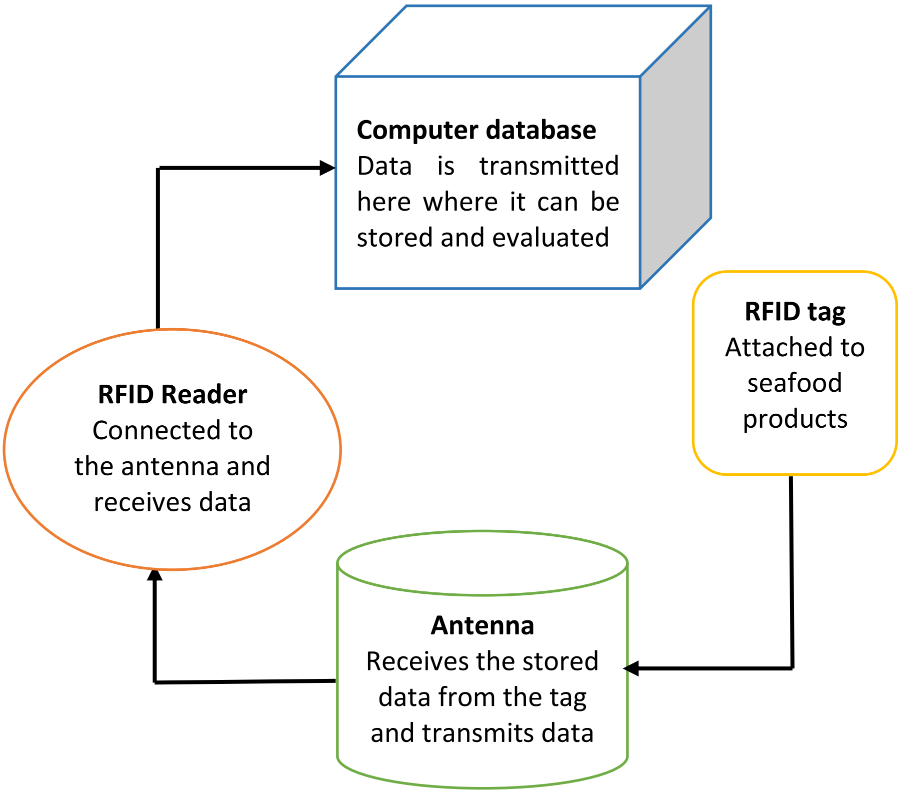

Figure 1. RFID process. Adapted from Rahman et al. (2021).

4.2 Quick Response (QR) codes

Quick Response (QR) codes are two-dimensional barcodes that can be printed on seafood packaging or labels. QR codes can be scanned by smart-phones or other devices to provide information about the product's origin, processing, and distribution. In reality, a QR code uses matrix bar-code technology. The QR Code can include text, video, ads, personal information, and more, allowing it to store significantly more data than a one-dimensional code (Kim and Woo, 2016). It is possible to read information from it, much like with matrix bar-codes (Demir et al., 2015). In order to assure the quality and safety of the products, the traceability connected with the use of the QR code may give information and transparency of the productive chains (Pieniak et al., 2011). The advantages of a QRC include great dependability (Chen et al., 2019; Waziry et al., 2023). The key advantage of this technology is its simplicity, since it simply requires the use of a Smartphone to scan the code in order to access the digitally accessible data (Machado et al., 2019).

Also, the benefit of QR codes is that they can hold a significant quantity of data. Any type of digital information that can be imagined can be embedded, including text, video, business card information, personal information, advertisements, etc. (Demir et al., 2015). Information systems can be accessed using QR-Code technology to add products produced by sellers (Liantoni et al., 2018). In order to assure the quality and safety of the products, the traceability connected with the use of the QR code may give information and transparency of the productive chains (Pieniak et al., 2011).

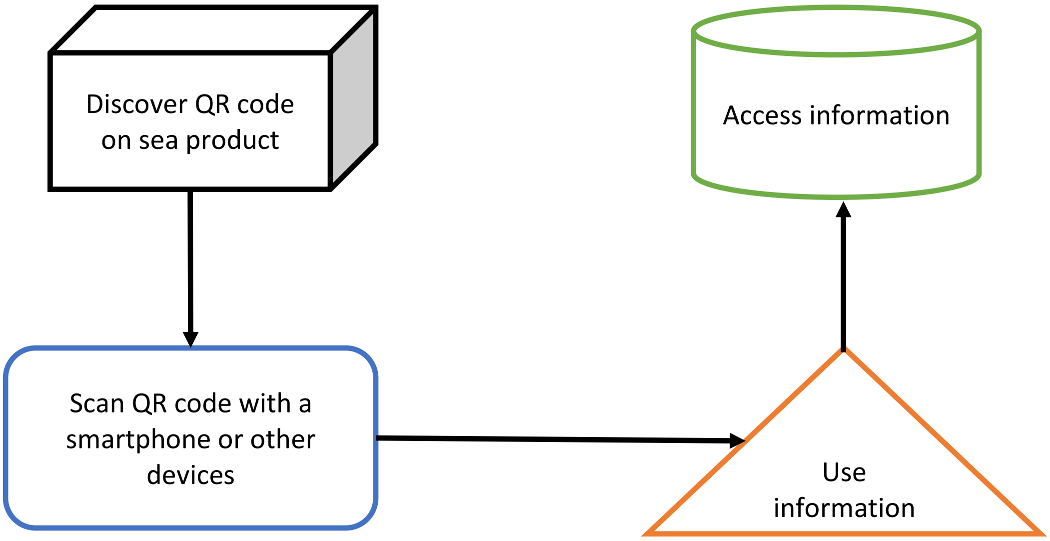

Figure 2. QR code process in seafoods. Adapted from Kochanska. (2020).

4.3 Blockchain technology

Block chain technology is defined as an open, distributed ledger that may effectively and permanently record transactions between two parties (Iansiti and Lakhani, 2017; Aydin and Yukcu, 2020; Friedman and Ormiston, 2022). The block chain technology also known as distributed ledger technology (DLT) was introduced in 2008 after the global financial crisis (Khan et al., 2022). Block chain technology is gaining traction as a cutting-edge invention that can promote sustainability in international supply chains (Saberi et al., 2019; Marsal-Llacuna, 2018; 2020). Block chain is an emerging technology in the agri-foods sector that has the potential to alter many facets of the agricultural industry (including fisheries and aquaculture) while also enhancing the safety and quality of agri-foods (Xu et al., 2020). By recording accountable information about food sustainability at all stages of the supply chain and enabling supply chain actors to query and verify specific food products, block chain, an emerging paradigm for immutable information storage and sharing, has the unique potential to improve sustainability communication (Cao et al., 2023). A decentralized digital ledger called a block chain can be used to securely and openly record and trace transactions. The supply chain can be made transparent and accountable by using block chain technology to produce a tamper-proof record of seafood products from their point of origin to their final destination. Researchers and professionals are becoming more aware of how block chain technology may inform and enhance the sustainability of the food supply chain (Cao et al., 2023). Block chain has arisen in this context as a promising technology that enables users to efficiently and effectively record the origin and movement of items as well as to totally eliminate or greatly reduce serious food fraud. Consumers can benefit from this development by receiving up-to-date, confirmed information in relation to the sources and delivery options of their purchases (Treiblmaier and Garaus, 2023). Applying block chain technology in seafood traceability could be beneficial as it could enhance higher automation in supply chain, lead to transparency and fraud protection. It also leads to positive influence on consumers, food authenticity, quality assurance and routine traceability (Patel et al., 2023). Furthermore, it can result in a decentralized network, a trustworthy trading system, making data much safe and unchangeable. . While different chain stakeholders have differing levels of adoption of this technology, implementing blockchain involves financial, technological, and organizational challenges (Sander et al., 2018; Kouhizadeh et al., 2021; Tolentino-Zondervan et al., 2022).

4.4 Electronic monitoring systems

Electronic monitoring, which is referred to as an integrated system of cameras and sensors on fishing vessels, can produce a thorough account of fishing activity that can help with fisheries management and guarantee that rules are being followed (Ruiz et al., 2015). Electronic monitoring systems can be used to track the movement and location of fishing vessels, and to monitor their catch and by-catch. Electronic monitoring systems can provide real-time information about the fishing activity and can help ensure compliance with regulations and sustainability standards. However, EM stands out due to the depth of data it can supply on fisheries activities and its thorough accountability.

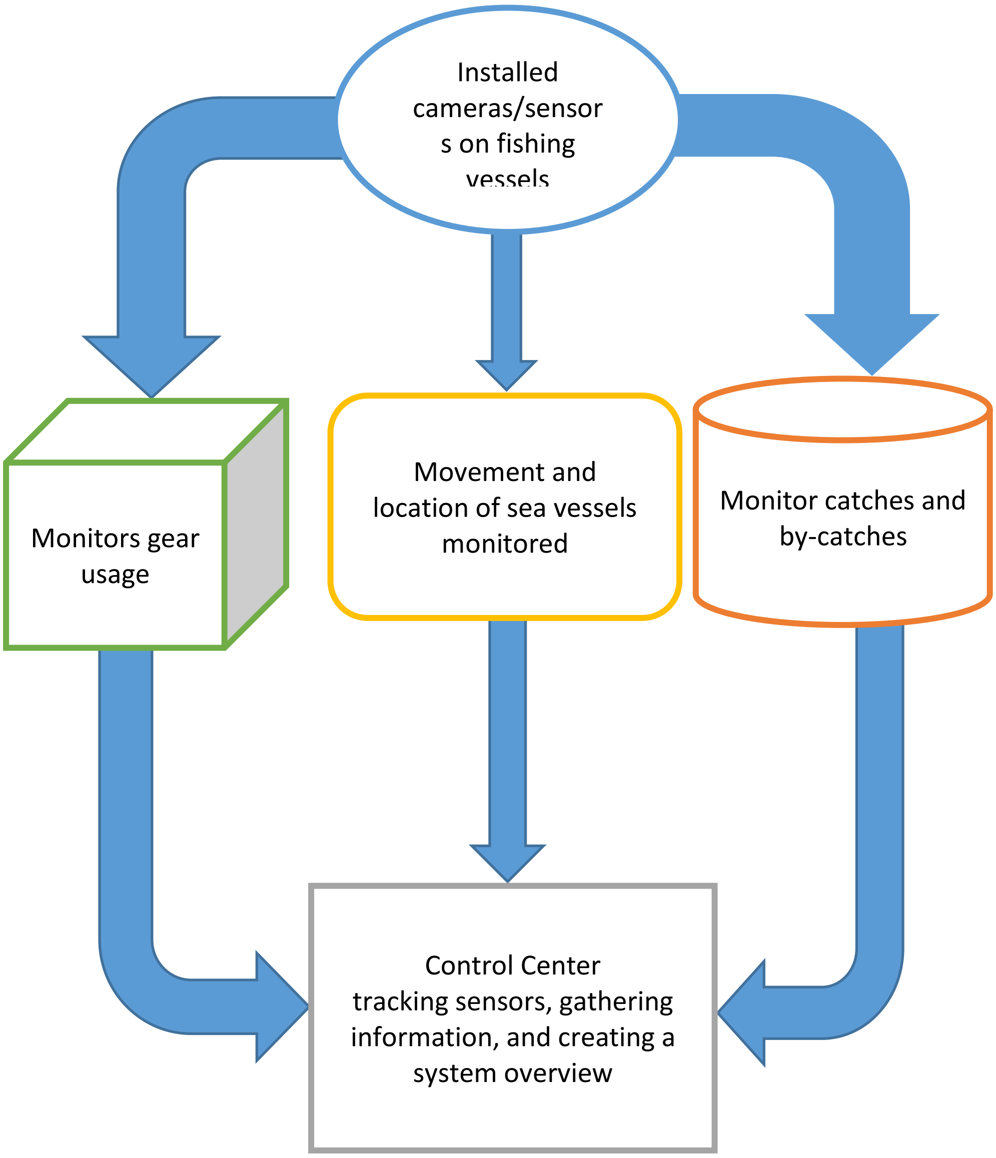

Figure 3. Electronic monitoring process in Seafoods. Adapted from van Helmond et al. (2020)

4.5 Digital twin

Grieves. (2014) initially proposed the digital twin concept. A reasonable definition of a digital twin is one that incorporates physical feedback data with artificial intelligence, machine learning, and software analysis to create a digital simulation within an educational platform. Despite differences in definitions, all definitions have three major elements namely; virtual space, physical space, and their connections of data and models (Liu et al., 2021). A digital twin is a virtual representation of a physical system that includes the environment and operational procedures and is updated by information exchanged between the physical and virtual systems. It is a gadget that constantly connects its virtual and physical equivalents (the twin) (Van der Burg et al., 2021; Neethirajan and Kemp, 2021; Melesse et al., 2023). The aim of digital twin is to characterize the behaviour of physical entities by leveraging on their virtual replica in real time (Liu et al., 2022). With the data fusion of each module, the digital twin keeps track of the state of the physical model in real time, which aids in the optimization and decision-making of physical items (Söderberg et al., 2017).

Digital twins are more responsive as a result of two-way communication. In order to automate and display the information to the human component in a way that is simple to understand, it is critical to capture expert decision making (Dyck et al., 2023). Using digital twins, physical and virtual items are combined in an effort to track and enhance resources and business operations (Autiosalo et al., 2020; Jones et al., 2020; Verdouw et al., 2021). Digital twins aid in identifying the post-harvest change of food quality that results, which is mainly unexplored. For exporters, retailers, and consumers, digital twins give data that may be used to make informed decisions about logistics and marketing, such as how long each shipment's shelf life will last (Defraeye et al., 2021). The twins also aid in the diagnosis and forecasting of potential supply chain issues that could lower food quality and result in food loss. In order to decrease retail and domestic food losses, twins may even recommend preventive shipment-tailored interventions (Defraeye et al., 2021). The visibility of the supply chain and the process monitoring would be significantly impacted by the deployment of digital twin technology in seafood traceability and management (Lezoche et al., 2020; Burgos et al., 2021; Agrawal et al., 2021).

5. DATA SOURCES FOR SEAFOOD TRACEABILITY

Data has been the foundation of the seafood industry and will continue to be. Obtaining the right information is an important step for traceability. Establishing or identifying reliable data sources is one way to increase openness. Based on this backdrop, the various sources of data that can be used to trace seafood products, such as catch data, vessel tracking data, and processing plant data are discussed in this section. In addition, advancements in technology, such as the Internet of Things (IoT), which keep making it easier to collect and analyze data is briefly discussed.

5.1 Sources of data for traceability

5.1.1 Catch data

Information on the fish or other marine animals that are caught by fishermen is referred to as catch data. The species, weight, and location of the catch, as well as details on the fishing boat and its crew, can all be included in this data. Catch information is crucial for tracking seafood items because it might reveal the product's origin and method of capture. Fishermen can collect catch data manually, or sensors and other technologies can do it automatically.

5.1.2 Vessel tracking data

Data on the movements of fishing vessels as they travel to and from fishing grounds is referred to as vessel tracking data. The location, speed, and direction of the vessel, as well as details on the weather and sea state, can all be included in this data. In order to trace seafood goods, vessel tracking data is crucial since it may be used to identify the product's origin and whether it was caught lawfully or illegally. Different technologies, including as satellite-based systems and automatic identification systems (AIS), can be used to gather data on vessel tracking.

Vessel monitoring systems (VMS) and the AIS can be used to track vessels (Orofino et al., 2023) in order to generate valuable information that are needed for seafood traceability. Vessel tracking can inform best practices, promote the fulfilment of important commitments, and improve transparency and traceability in operations in the seafood (Seafood Business for Ocean Stewardship, 2021).

5.1.3 Processing plant data

Information about the preparation and packaging of seafood items is referred to as processing facility data.

The location of the processing plant, the type and amount of the product, and the date and time of processing are just a few examples of the information that might be included. Data from the processing plant is crucial for tracking seafood items since it can be used to establish the chain of custody starting with the moment the product was captured and ending with the moment it was packaged and sent. Data collection in processing plants can be done manually or automatically using sensors and other technologies.

6. ARTIFICIAL INTELLIGENCE FOR SEAFOOD QUALITY PREDICTION AND OPTIMIZATION

A computing technology known as artificial intelligence (AI) aims to imitate human skills to sense their environment, analyze information, make decisions, and take actions to accomplish predetermined goals to varying degrees (Manning et al., 2022). Also, AI refers to a system for data analysis that automates skilful model creation (Li, 2021). Again, Chrispin et al. (2020) defined AI as the future made from pieces of the past. AI can take the role of human intelligence in problem-solving and decision-making (Kutyauripo et al., 2023). The ability of AI to accurately interpret external data, learn from it, and use that learning to accomplish specified objectives and tasks is one of its specialities (Hainlein and Kaplan, 2019). AI is increasingly being used to establish standards for current behaviours and the outcomes of those practices in the food sector and forecast how these elements will affect food supply and quality in the future (Karanth et al., 2023). The agriculture industry of which seafoods and crop production as well as harvesting and marketing are inclusive has seen tremendous improvement through the use of artificial intelligence (Goel et al., 2022). As a result of issues such as food safety, quality control, and classification as well as food sorting, the application of AI in the food industry keeps growing (Mavani et al., 2021).

Several AI are applied in the Prediction and Optimization of the quality of seafood. These includes neural networks, deep learning, machine learning, etc.

In this section, AI applied in predicting and optimization of seaweed quality are discussed. Special emphasis is laid on their description, advantages, disadvantages and application in seafood industry.

6.1 Machine learning

Computer science's sub-field of machine learning is categorized as an artificial intelligence technique (Chawla et al., 2023). Machine learning is the ability of a computer to learn without being taught for a particular job (El Naqa and Murphy, 2015; Anwar et al., 2023). Machine learning could either be supervised or unsupervised (Anwar et al., 2023). Samuel (1959) initially proposed the concept of machine learning, which is the study of how to enable computers to learn without being explicitly programmed. A subfield of artificial intelligence called machine learning makes use of a variety of factual and probabilistic approaches to teach computers how to discover hidden patterns (input-output linkages) in vast and frequently noisy data sets (Okafor et al., 2023). According to purposes and training methods, machine learning can be categorized into three broad approaches namely unsupervised learning, supervised learning and reinforcement learning (Chung et al., 2023). It has the benefit of allowing models to address issues that explicit methods cannot, and it may be used to a variety of fields (Chawla et al., 2023). M5-Prime regression tree, multiple linear regression, support vector regression, perceptron multilayer neural networks, and k-nearest neighbour are examples of machine learning employed in enhancing food. The development of selective fishing gear that lowers the accidental capture of non-target species can be facilitated by the application of machine learning algorithms. In addition to protecting biodiversity, this lowers fishermen's financial losses (Rossi, 2022). By analyzing data on the behavior and needs of individual species, machine learning algorithms enable individualized care while consuming the fewest resources possible. This strategy improves the industry's overall sustainability and efficiency (Neethirajan, 2020). It has proven possible to use machine learning to create chemometric discrimination tools by utilizing chemical pollutants and metal isotope ratios in eastern oysters (del Rio-Lavín et al., 2022)

6.2 Deep learning

An artificial neural network-based representation learning algorithm known as "deep learning" is a sub-field of machine learning (Deng and Yu, 2014). With numerous successful applications in image processing, speech recognition, object detection, and other fields, deep learning has established itself as a cutting-edge method for big data analysis (Zhou et al., 2019). Deep learning has demonstrated substantial benefits in automatically learning data representations, transfer learning, coping with the enormous amount of data, and achieving improved performance and higher precision (Ng et al., 2015; Kamilaris and Prenafeta-Boldu, 2018). Also, Jeevanandam et al. (2022) reported that due to the ability of deep learning to feature learning based on multi-layer artificial neural networks, it has received significant attention. In recent years, automatic identification of fish, sizing as well as counting has been performed by applying deep learning (Ovalle et al., 2022). Ovalle et al. (2022) investigated various Deep Learning (DL) based length estimation and species identification techniques. On the one hand, they modified the Mask R CNN method to the problem of fish species identification for the instance segmentation task. On the other hand, the length of each individual was estimated using the MobileNet-V1 convolutional neural network. The findings demonstrated that both the identification and length estimate algorithms can accurately measure the catch when individual overlap is modest to low. When there is a lot of overlap between individual fishes, the outcomes still need to be improved. The majority of recent studies on feeding decision-making with deep learning have focused mostly on image analysis. Machine vision can be used to create a better feeding plan that considers fish behavior. Such a device can stop the feeding process at more reasonable times, reducing labor waste and improving fish health (Zhou et al., 2018). Furthermore, behavior serves as a useful point of reference for fish welfare and harvesting. Relevant behavior monitoring can provide a nondestructive understanding and an early warning of fish status, especially for uncommon actions. Determining the condition of fish and deciding when to collect and feed them depend on real-time behavior monitoring. The ability of DL techniques to recognise visual patterns is considerable. employing DL to analyse behavior. RNNs, in particular, can solve the aforementioned issue successfully because of their strong modeling capabilities for sequential data (Yang et al., 2021).

6.3 Neural networks (NN)

Machine learning's neural network sub-field uses algorithms to analyse data and create abstractions that mimic thinking (Ma et al. 2022). It processes data, decodes spoken language, and visually identifies objects using multiple layers of algorithms. Each layer transmits information, with the output of one layer serving as the input for another (Zhou et al., 2019). As neural networks, one type of machine learning model, are naturally capable of handling such nonlinear phenomena, they have emerged as the model of choice for many researchers (Bali and Singla, 2021). In addition to achieving forward tracking and varied tracing for products in the supply chain, neural networks also assess food quality based on the related traceability data stored in the system. This can give consumers and related stakeholders more information, such as the product's quality level, to improve the consumer experience (Wang et al., 2017). It comprises a straight forward perceptive that calculates the weighted total of its inputs and outputs using mathematical operations (Zhu et al., 2021). The way an information flows across the network as well as the number of connection weights is determinant upon the architecture of the NN models (Maier et al., 2000). Multilayer perceptron which possess only three layers in most types of feed forward NN is the most widely and commonly used architecture (Csábrági et al., 2017).

Neural networks have a number of benefits, including high noise tolerance, the ability to generalize, and superior adaptation characteristics (Guiné, 2019). Incomprehensible model behavior, multi-source heterogeneous data, a lack of software with a food scientist-friendly interface are only a few of the primary issues faced by neural networks (Ma et al., 2022).

Hyperspectral photography was used by Liu et al. (2019) to investigate the use of a convolutional neural network for seafood species recognition. In this study, the usage of a convolutional neural network (CNN) to detect various seafood species using hyperspectral data is investigated. According to the study, CNN had a high degree of accuracy in its ability to identify various species of seafood.

In a similar vein, Chang and colleagues in 1999, investigated the use of neural networks to forecast shellfish demand. This study explores the use of a neural network to forecast consumer demand for various clam varieties based on previous sales information. The study discovered that the neural network could accurately estimate demand, and that this method might be helpful for supply chain management optimization.

Hussaine et al. (2020) investigated the use of blockchain and neural networks for seafood traceability. This study explores how to enhance seafood management and traceability using neural networks and blockchain technologies. The study suggests using neural networks to assess data on different types of seafood, fishing areas, and other variables.

7. APPLICATION OF AI IN ANALYSIS OF LARGE DATASETS OF SEAFOOD QUALITY

The Internet of Things (IoT) and recent developments in sensor networks have allowed for the collection of vast amounts of data (Rahmani et al., 2021). Big data has been created across many different locations via digital tools, platforms, apps, and human communications (Daniel, 2019; Luan et al., 2020).

More effective techniques with high analytical accuracy are required for the investigation of such vast amounts of data (Rahmani et al., 2021).

The main advantages of the big data revolution are frequently seen to be the extraction of useful knowledge and workable patterns from data (Mayer-Schönberger and Cukier, 2013; Jagadish et al., 2014). Big data analytics make use of a range of technologies and methods, including signal processing, image recognition, text analytics, social network analysis, data mining, visualization, predictive modelling as well as natural language processing (Chen and Zhang, 2014). The application of these AI technologies in the of large data sets in seafood quality monitoring and evaluation is discussed in this section.

7.1 Image recognition

Artificial intelligence is becoming increasingly proficient at applying image recognition, a digital picture or video procedure for identifying and detecting an object or feature (Bhardwaj et al., 2021). Based on visual signals including colour, texture, and shape, AI algorithms can be trained to identify various varieties of seafood and assess their quality.

An essential approach to verify the quality of fish is to analyze its color changes using imaging software, which is a non-hazardous, non-destructive common tool for analyzing data based on photography (Menesatti et al., 2010). One of the key approaches for enhancing raw photos from diverse sources, such as cameras or satellite sensors, space probes, aircraft, etc., is digital image processing (Awalludin et al., 2020). The use of a computer algorithm to perform image processing on a digital image is known as digital image processing. It deals with edge detection, edge sharpening, conversion, blurring, recognition, etc (Awalludin et al., 2020). The initial image's quality could be improved with the aid of image processing techniques, which also prepared the image for automated interpretation. The input images, pre-processing, segmentation, feature extraction, and classification of images are all dealt with by image processing techniques (Gamage, 2017).

Some studies have been conducted on the use of image recognition for monitoring seafood quality (Muhamad at al., 2009; Wang et al., 2013; Duta et al., 2016). Of these, Muhamad at al. (2009) proposed a fuzzy logic-based method for classifying the freshness of fish whilst Wang et al. (2013) suggested a regression-based technique on depending on the eye from samples of fish. Fuzzy logic technology was used in a 2009 study by Muhamad and colleagues to classify fish freshness based on image processing. To categorize the freshness of the fish in this study, the RGB color image processing data with a focus on the eye and gill of the fish was analyzed and simplified. A fuzzy logic technology has been applied to this goal. There are two different kinds of fuzzy input techniques that have been discussed: and involves two inputs, one of which is the mean RGB value for both the eye and the gill. There are six inputs where the input is an RGB value for the eye and gill, respectively. Results show that produce better results when compared to categorizing seafood freshness.

In order to cut expenses and time-consuming human inspection, the development of automatic fish sorting methods utilizing image analysis has been studied (Strachan and Kell, 1995). A study by Zion et al. (1999) created an image processing system based on moment-invariants combined with geometrical considerations for discriminating between photographs of three species of fish.

7.2 Predictive modelling

Predictive modelling is a crucial area of research in the seafood industry. For the food industry to increase productivity and minimize waste, the use of mathematical predictive models to evaluate microbial behaviour under various environmental circumstances is an intriguing approach. Predictive modelling can be used in a variety of contexts to improve the safety and quality of seafood, including quantitative (microbial) risk assessment, food chain modelling, quality and safety management, modelling of food processes, sampling, and plant design (Vasilis et al., 2013). Application of mathematical modelling for predicting shelf life necessitates adequate product rotting mechanism information has been reported (Koutsoumanis and Nychas, 2001). AI is able to find patterns and predict future seafood quality based on variables like temperature, water quality, and storage conditions by evaluating vast datasets of seafood quality metrics. One key field in the development of the food industry is predictive modelling (Membré and Lambert, 2008). Predictive models and their applications can be categorized into three namely; incident support to estimate the grade of impact on consumer safety or product quality, supporting food safety decisions that need to be made when implementing or running a food manufacturing operation and product innovation for assessing the rate of microbial proliferation (Calanche et al., 2020).

Some studies have been conducted to evaluate predictive modelling as a tool in the seafood industry (Koutsoumanis, 2001; Calanche et al., 2020; Giarratana et al., 2020; Garcia, 2022; Giarratana et al., 2022). Predictive modelling approaches have been used to determine the growth of pathogenic microorganisms in seafoods (Dalagaard et al., 2002).

According to Calanche and colleagues in 2020, the physico-chemical and microbiological parameters had a satisfactory correlation. The establishment of a shelf-life of 10 days, which corresponded to a poor grade (according to the European Community's system of grading fish for marketing purposes) with a freshness index below 50%, was made possible through sensory analysis and microbiological counts. Gill and flesh texture were the characteristics most susceptible to spoiling while storage in ice, according to sensory profiles. Following practical validation, the predictive models for the freshness index (%) and ice storage duration (h) showed an accuracy close to 90%.

Based on dynamic temperature conditions and a subsequent statistical analysis of the outcomes, Giarratana et al. (2022) built a deterministic mathematical model. The shelf-life of Atlantic mackerel was predicted using this model at certain storage temperatures. A total of 60 fresh fish were divided into two groups and held in ice for 12 days, one group at a constant temperature of 10.5°C and the other at a variable temperature of 1–7°C. At regular intervals, each fish had a microbiological examination and a sensory assessment using the Quality index method (QIM). After 9 days of storage for Group A and 3 days for Group B, a critical value of 6

Log cfu/g of spoilage bacteria (mostly psychoactive) linked with a considerable degradation of the sensory qualities was exceeded. By modelling the Quality index method (QIM) as a function of the behaviour of the spoilage bacteria, a trustworthy prediction of fish freshness was made possible. The spoilage bacteria load was converted into a Quality Index score using a coefficient of correlation.

In varied isothermal circumstances between 0° C and 15° C, Koutsoumanis (2001) observed the behavior of the natural microflora of Mediterranean gilt-head seabream (Sparus aurata) during aerobic storage. The influence of temperature on pseudomonad growth was modeled using a Belehradek type model employing the growth data of pseudomonads, which were established as the particular spoiling organisms of aerobically preserved gilt-head seabream. For the maximal specific growth rate (max) and the lag phase (tLag), the nominal minimum temperature parameters of the Belehradek model (Tmin) were found to be 11.8 and 12.8°C, respectively. By contrasting predictions with actual growth in dynamically changing tests, the model's applicability in forecasting pseudomonad growth on fish at shifting temperatures was assessed. Utilized were temperature scenarios created in the lab and simulations of actual temperature profiles seen in the fish chill chain. As comparison indices, bias and accuracy factors with corresponding ranges of 0.91 to 1.17 and 1.11 to 1.17 were utilized. For all temperature profiles studied, the average percent difference between shelf life experimentally measured by sensory analysis and shelf life projected based on pseudomonad development was 5.8%, demonstrating the model's accuracy in predicting fish quality under realistic circumstances.

7.3 Data clustering/Cluster analysis

A variety of exploratory multivariate statistical techniques that seek to isolate homogeneous groupings within a data set are collectively referred to as cluster analysis (Daniel and Gastón, 2014). A data-driven technique called cluster analysis is used to group people with comparable traits into groups. Based on quality criteria, AI can group together similar types of seafood, enabling researchers to find shared traits and potential quality-affecting variables. Since it may be used to categorise a set of samples according to many different features, cluster analysis is significant. Cluster analysis can also be used to more effectively evaluate huge data sets from instrumental measurements (Daniel and Gastón, 2014). In order to produce food products for particular consumer segments, cluster analysis is frequently used to identify groups of customers with varied preference patterns based on their liking of a collection of samples (Yenket et al., 2011).

Data mining, document retrieval, image segmentation, and pattern classification are only a few exploratory patterns analysis, grouping, decision-making, and machine learning applications where clustering is helpful (Jain, 2010). Clustering has been used to investigate genome data (Baldi and Hatfield, 2002) as well as group services delivery engagements for workforce management and planning (Hu et al., 2007).

7.4 Drone technology

Drones are revolutionizing land-based businesses; shops are looking into drone-based delivery systems, and realtors are using them to take aerial images of properties that are for sale. Underwater drones could bring about a similar transformation in the marine resources field by giving researchers eyes beneath the waves so they can monitor water quality and inexpensively remedy equipment issues (Whitt et al., 2020). These underwater drones will test dissolved oxygen levels and other physical and chemical data, and they will be outfitted with cameras to identify tears in nets before they get too serious, according to the drone creators (Orlowski, 2017). Divers may be put in danger during these checks, but the underwater drone is resistant to bad weather and much adverse weather conditions (Xiang et al., 2022). By using the drone's data on fish movements and environmental factors, fishermen may increase growth, reduce waste, and enhance accuracy. By examining fish stress levels, the data can also be utilized to reduce disease outbreaks and death (Fujita et al., 2018). Analyzing light conditions, on the other hand, can help control maturity and improve harvest quality (Ding & Ma, 2012). EyeROV TUNA, the first remotely operated underwater drone available for purchase in India, can send real-time footage of ships and other underwater structures to help with upkeep and repairs (Bagde & Pathan, 2023). The drone's capacity to navigate to a depth of 50 meters and take real-time HD video photos for underwater analysis has saved the usage of more costly and risky human examination by divers. One of the most cutting-edge systems, fishSHOAL, uses robot fish to find sources of underwater pollution (Müller-Schloer & Tomforde, 2017).

7.5 Data mining

Data mining is the technique of computing that identifies patterns in big data sets and extracts pertinent information (Kubat et al., 1998). It entails the application of both straightforward and sophisticated techniques, such as k-means clustering, k-nearest neighbour classification, support vector machine binary classifiers, dynamic prediction, modeling, artificial neural networks, and algorithm architecture, for the purpose of extracting useful data from relational, transactional, object-oriented, spatial, temporal, and relational databases, as well as from global information systems (Liao et al., 2012). Association, evolution, generalization, classification, characterisation, clustering, data visualization, pattern matching, and meta-rule guided mining are the main categories of data mining techniques (Gladju et al., 2022).

7.6 Robotic cages

For use in the open ocean, robotic cages are complete cages equipped with cameras, sensors, feeding and recirculation systems. A cage that fishermen can place their fish in before setting it adrift in the ocean (Føre et al., 2023). Brass mesh creates a cage, which prevents biofouling or the growth of algae and barnacles on submerged objects. By doing this, drag, and the requirement to clean the cages are reduced (Bagde & Pathan, 2023). Aquapods (Small Amphibious Robots with Sampling Capabilities) are a common name for robotic cages. These monitoring tools can be applied to aquaculture and exploration (Mackowiak, 2019). Data and AI will be necessary for commodity seafood markets, such as those for prawns and salmon, where international competition determines the price (Engle et al., 2016).

8. RESEARCH GAPS AND FUTURE OUTLOOK

Economic, technological, policy and ecological factors would greatly determine the contribution of seafood in meeting future food supply globally. A crucial issue that impacts both the commercial viability of the seafood business and the sustainability of seafood resources is the reduction of losses and wastage in seafoods. One viable answer to this challenge is the use of smart tools and biosensors based on artificial intelligence (AI) to enhance seafood processing and storage.

Although some progress has been made with respect to the use of AI based smart tools and biosensors in ensuring seafood are managed sustainably, lots of research gaps exist. There is therefore the need to fill these gaps to maximize the potential of biosensors and smart tools in reducing wastage and losses along the seafood value chain.

Analyzing and processing data in large quantities or amounts could be problematic. In this regard, researchers should focus on looking at tools that can analyze large amounts of data generated from the use of biosensors and smart tools based on artificial intelligence. In solving this challenge, there will be the need to conduct further studies to develop artificial intelligence algorithm that has the potential to produce insights that are actionable and can interpret complex data sets for sustaining production of seafoods.

Researchers should focus their studies on the utilization of deep learning, advanced molecular analysis methods like chromatography, electrophoresis, and spectroscopy, as well as genome characterization, to provide a revolutionary method for examining the quality dynamics of food ingredients.

Ability to detect fish spoilage which leads to great loss and wastage very early is important in ensuring food security. In this regards, it is important produce biosensors that can accurately detect early characteristics of contamination in seafood samples or seafood spoilage. Again it will be prudent to direct research towards development of biosensors that has the ability to detect varied range of microorganisms and compounds in seafood samples.

9. CONCLUSION

This review sort to highlight the role of smart tools and biosensors based on artificial intelligence in reduction of losses and wastage in seafood industry. The findings of this review demonstrate that a wide range of biosensors, grouped according to their modes of operation, can be used to assess the quality of seafood. These biosensors include microbial biosensors, optical biosensors, tissue-based biosensors, immunosensors, DNA-based biosensors, electrochemical biosensors, enzyme-based biosensors, optical biosensors, and piezoelectric biosensors. The most prominent of these biosensors are optical biosensors, electrochemical biosensors, and mechanical biosensors. Again, this study shows that a number of smart technologies are used for seafood traceability and management, including blockchain technology, quick response (QR) codes, data analytics, digital twins, and RFID tags. Data from the processing plant, vessel tracking information, and catch data are a few of the various data sources that can be used to track seafood products. The quality of seafood can be predicted and enhanced using artificial intelligence methods like neural networks, deep learning, machine learning, and others. There is a need to fill research gaps in the creation of biosensors capable of identifying a wide range of bacteria and chemicals in samples of seafood, even though some studies have been conducted regarding the role of smart tools and biosensors based on artificial intelligence that could reduce losses. Studying the creation of biosensors that can accurately detect the earliest indications of seafood contamination or rotting is essential.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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