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Role and Importance of Digital Technologies in Fish Quality Analysis

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Fish, vital high-protein sources for a growing global population, face challenges due to the continuous depletion of wild stocks, affecting aquaculture's ability to sustain fish and seafood supply globally. Despite its diversity, aquaculture must innovate for sustainability, focusing on increased fish production, species selection, disease prevention, waste reduction, pollution control, and global employment. This article explores how digital transformation, utilizing technologies like ICT, IoT, Cloud-edge computing, AI, machine learning, immersive technologies, and blockchain, supports fisheries/aquaculture by enhancing operational efficiency in the global food chain and reducing waste, contamination, and fraud. Industry 5.0's shift emphasizes AI and robotics collaborating with the human mind for human-centric solutions. Highlighting the Quadruple Helix Hub's role (academic-industry-government-society), the article advocates a holistic approach to meet fishery industry needs by connecting fisheries with stakeholders. This includes specialist training, testing technologies, access to finance, and disruptive initiatives like Hatch Blue's aquaculture accelerator. The global connection of digital innovation hubs is crucial to mitigate risks from climate change, global pandemics, and conflicts disrupting fish and seafood production and supply chains. The adoption of digital technologies is essential for raising awareness throughout the value chain, facilitated through social marketing. Addressing challenges via the global digital transformation of the fishery and aquaculture industry aligns with various sustainable development goals outlined by the United Nations, focusing on disruptive technology applications.

INTRODUCTION

The consumption of fish is primarily driven by factors such as freshness, quality, and taste (Tomic et al., 2016). In recent years, the consumer market has shown a growing preference for high-quality seafood products that are resilient to diseases. Several crucial aspects contribute to the determination of fish quality, with safety, nutritional value, availability, freshness, storage, and processing methods playing significant roles (Yasin et al., 2023). Throughout the entire production chain, from harvesting to food preparation, various factors can impact the quality and freshness of fish. Recognized as a nutritious meal, fish plays a pivotal role in human wellness due to its rich content of essential nutrients, vitamins, and proteins (Jose et al., 2022). The presence of protein, omega-3 fatty acids, and vitamins contributes to the health benefits associated with consuming fish. Additionally, the affordability and freshness of fish make it a popular choice among consumers (Mitra et al., 2021). Freshness, in particular, enhances the nutritional quality of fish, but determining its freshness can be challenging for consumers during the purchasing process.

The conventional method of assessing fish freshness involves touching and squeezing the fish to evaluate the flexibility of its body, with higher elasticity generally indicating freshness (Yasin et al., 2023). However, this approach poses a risk of food contamination with harmful microorganisms. The quality of fish is heavily influenced by how it is handled, processed, and stored from the moment of capture until consumption. Maintaining the highest quality post-harvest requires specific temperature control (Dutta et al., 2016). Advancements in technology have led to attempts to establish more reliable methods for measuring and assessing seafood freshness. Criteria for determining freshness encompass sensory, physical, chemical, and microbiological aspects. Techniques such as rapid protein liquid chromatography and hyperspectral imaging are also considered. The coloration of the fish's eye region has been identified as strongly correlated with storage duration, providing a visual indicator of freshness (Ghaly et al., 2010).

Fish undergoes decomposition through two primary sources once it begins: biological spoilage and chemical spoiling. Bacteria entering the fish through its gills degrade tissues and organs, leading to biological spoilage (Yasin et al., 2023) Chemical spoilage, on the other hand, results from chemical interactions, causing disagreeable odors and affecting flavor. Fish spoilage involves changes in color, odor, taste, and flesh texture. Increased pH and nitrogen substances promote the multiplication of microorganisms, affecting various parts of the fish after the initial spoilage stage (Alasalvar et al., 2010). Observing changes in gill coloration from brilliant pink to dark red or yellowish-red indicates the transition from fresh to stale. Generally, freshness is determined by the skin's changing color, shifting from bright and shiny to dull and less vibrant as freshness is lost. Factors influencing fish freshness include the hue of its flesh, with the color shifting from cream to yellowish, brown, and ultimately blue as the fish ages. This color variation serves as a key determinant of fish freshness (Suresh et al., 2021).

Literature related to DI in fish freshness

In the wake of the advancements in machine learning, the classification of fish has emerged as a critical field of study (Yasin et al., 2023). Numerous research endeavors have been dedicated to identifying distinct fish body parts, employing various techniques for segmenting fish gills and eyes, such as observing color alterations across different color spaces. The investigation of color shifts in fish gills and eyes has proven effective for detecting these anatomical features. Specifically, fish eyes and gills can be segmented based on color degradation in different hues, gills can be clustered for segmentation (Dutta et al., 2016), and diverse image processing techniques can be leveraged to segment fish gills, utilizing color degradation or clustering methodologies (Issac et al., 2017).

Pioneering the application of the You Only Look Once (YOLO) method, Muri Knausg˚ard et al. utilized a Convolutional Neural Network (CNN) within a Squeeze-and-Excitation (SE) architecture to categorize each fish without the need for pre-filtering. Given the scarcity of temperate fish training data, transfer learning was implemented to enhance classification accuracy. Their model achieved an impressive 99.27% pre-training model accuracy and 83.68% and 87.74% post-training model accuracy without image augmentation, using the Fish4Knowledge public dataset. Hu et al. identified three squid species through a deep learning model known as the "Improved Faster Recurrent Convolutional Neural Network." Metrics such as Accuracy, Intersection-over-Union, and Average Running Time were utilized for evaluation, with 600 squid pictures taken against a uniform black background (Hu et al., 2020). Prasetyo et al. proposed "You Only Look Once version 4 tiny (Yolov4-tiny)" for recognizing fish body sections, indicating superior detection accuracy compared to other models on the Fish and Fish Parts Detection (FFPD) dataset. The model's updated version, WCL-Yolov4-tiny, demonstrated Precision, Recall, AP, and mAP metrics of 97.48%, 93.3%, 94.07%, and 92.38%, respectively, allowing for precise detection of fishes, their eyes, and tails (Prasetyo et al., 2022).

Wu et al. (2022) introduced a novel CNN_LSTM methodology for determining fish freshness across varying temperature conditions, highlighting the effectiveness of a feature descriptor based on data from pre-trained models like VGG16 and AlexNet. Various deep learning methods, including Artificial Neural Network (ANN), Convolution Neural Network (CNN), and Deep Learning Network (DLN), are employed to categorize extracted characteristics (Kaya et al., 2018). Recent articles have also explored the use of support vector machines (SVM) and other machine-learning approaches (Sayed et al., 2018). In their study, Abu Rayan et al. (2021) proposed a mixed deep-learning model-based technique for classifying fish freshness using image processing and Nile Tilapia as a model fish. The suggested model, constructed by extracting features based on the VGG-16 neural network architecture and bi-directional long short-term memory (LSTM), achieved an impressive 98% accuracy when tested against the dataset. Distinguishing characteristics of fresh and stale fish, such as bright, black eyes, white skin, and undamaged fins versus gray eyes, red skin, and a swollen belly, were outlined.

Dutta et al. (2016) proposed a non-destructive image processing method to determine fish freshness, utilizing wavelet transformation, auto-segmentation, and the Haar filter to extract tissue characteristics. Atasoy et al. (2015) built a fish freshness system using an electronic nose with eight metal oxide gas sensors, achieving a 98.94% success rate through the utilization of Artificial Neural Networks (ANN) for classification. To address background variant problems, Jany Arman et al. presented a fish classification method incorporating salient object recognition, yielding high test results on models 1 and 2. Issac et al. (2018) provided an automated approach for gill segmentation in fish images, achieving a notable correlation of 92.4% with expert-sourced ground truth findings over a 13-day imaging period involving four different fish species. Kaladevi et al. (2021) proposed a deep learning methodology for enhancing sardine fish freshness detection precision, utilizing a dataset of 1049 fresh and 1078 stale sardine fish images. The implemented DCNN yielded promising performance metrics, including a precision of 99.5%, a true positive rate of 96.2%, true negative rate of 92.3%, a positive predictive value of 92.6%, negative predictive value of 96%, and an F1 score of 94%. The study by Kaladevi et al. (2021) included Table 1, which compiled various methods for detecting fish freshness, detailing image counts, categorization methods, applied techniques, and resulting accuracy ratios from previously conducted experiments. Abu Rayan (2021) acknowledged the potential use of alternative classification methods, encouraging new studies to explore different AI methodologies for improved results.

CONCLUSION

Assessing the freshness of fish has long been a human skill, relying on sensory observations like examining the eyes, smelling, and inspecting gills. However, replicating this nuanced task for machines poses a considerable challenge. This study proposes an innovative method employing deep learning techniques to determine the freshness of fish. The research involved the utilization of a dataset to classify fish body freshness into two distinct categories: fresh or stale. Unlike many previous studies that employed various methods such as chemical or biological approaches and different sensor types, this study specifically focuses on employing deep learning algorithms for freshness detection. Notably, what sets this study apart is its unique approach of using the same dataset as previous research without any modifications. Despite this continuity, the study achieved a significantly higher success rate compared to prior efforts, surpassing the performance of the VGG-16 neural network architecture and the Bi-directional Long Short-Term Memory model utilized in previous studies. This success highlights the effectiveness of alternative methods proposed in this research, showcasing the potential for enhancing machine-based freshness assessment in the context of fish quality.

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