INTERNATIONAL RESEARCH IN BIOLOGY-II

COMPARISON OF TRADITIONAL AND ARTIFICIAL INTELLIGENCE APPLICATIONS

Editors
Prof. Dr. Cengiz Mutlu, Lect. Dr. Selda Palabıyık

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TABLE OF CONTENTS

PREFACE

Nowadays, the widespread use of artificial intelligence applications in all areas of life is remarkable. Artificial intelligence is preferred, especially in areas that have problems in accessing data, as it offers an alternative approach. Notably, artificial intelligence applications can reduce the unit costs of high-budget research, saving time, personnel, and analyses, as well as reducing the carbon footprint of the workflow process. Moreover, its compatibility with the sustainable and green approach to ecosystem fundamentals is well-established. However, by appropriately processing the data obtained through conventional methods, it is possible to make these developments more efficient, even with higher accuracy and applicability. Therefore, combining both approaches during this transition process can lead to a more effective one.

This book provides a comprehensive overview of the field of hydrobiology, which holds a significant position within the field of biology in light of recent developments. The water and aquatic resources play a crucial role in supporting the living activities of the global ecosystem. They can affect the formation of life on earth, biodiversity, climates, and even the sociological and psychological attitudes of societies. Evaluating a sustainable ecosystem through the lens of a single health principle is a more practical approach. It is therefore a more realistic approach to assess a sustainable ecosystem from a single health principal perspective. Within the scope of traditional and artificial intelligence applications, the book content details both theoretical and practical approaches to fish, which hold a significant position in the food pyramid. This approach provides a detailed projection of the current development process.

Prof. Dr. Cengiz MUTLU

Lect. Dr. Selda PALABIYIK

CHAPTER-I

ARTIFICIAL INTELLIGENCE APPLICATIONS: SUSTAINABILITY OF FISH STOCKS

Hakan Işık[1], Selda Palabıyık[2]

The proper development and effective implementation of the fisheries management laws that ensure the sustainability of the marine resources and the fisheries is one of the biggest challenges to the policymakers in the present world (Ovalle et al., 2022). There is a need to enhance the sustainability and productivity of aquaculture because the issues like population growth, climate change, and declining capture fisheries are being felt across the globe (Ramírez-Coronel et al., 2024).

Intelligent technologies have helped the aquaculture sector in many ways such as reducing the cost of labor, increasing production and enhancing the environmental impact. One of the most popular types of artificial intelligence is machine learning which is a computer program that contains an algorithm that is able to 'learn' from data that has been put into it. There has been a lot of focus on the use of machine learning in smart aquaculture to date with applications including species identification, disease identification and detection, sorting-grading, and size, length and weight estimation (Vo et al., 2021; Akkan et al., 2024). The condition and performance of the fish stocks can then be assessed in order to gain a better

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understanding of the dynamics of the population and to facilitate the right fishing measures. It is also important to establish the age structure of the fish population should also be estimated (Carbonara and Follesa, 2019; Sigurðardóttir et al., 2023) ANN has been identified to be effective in solving various problems that are current and relate to the sustainable development goals (Gue et al., 2020). Currently there is a global push towards digital reporting of catches in order to support sustainable fishing. Nevertheless, since it is too laborious to record the basic catch data such as fish counts, length measurements and species identification manually, there is an increasing need for automation. The Convolutional Neural Networks (CNNs) have recently gained much attention in various fields for the image recognition systems (Hasegawa et al., 2024).

The production of aquaculture products globally enhanced from 25.7 % in 2000 to 46 % in 2018. 62.5% of aquaculture production in 2018 was produced by continental aquaculture. The Food and Agriculture Organization of the United Nations (FAO) has identified aquaculture as one of the most viable businesses that can help reduce poverty and improve food security (FAO 2010; Bernal-Higuita et al. 2023). According to Ordoñez et al. (2020), accurate age determination of fish is essential for the management of fish populations in sustainable fisheries.

The application of big data and artificial intelligence in marine research is developing rapidly (Malde et al., 2020). Aquaculture and fisheries are looking for creative solutions to efficiently use water resources and biodiversity to meet growing human demand. This includes the integration of information technology, data science and artificial intelligence for production intensification, sustainable fishing and mechanisation/automation. In addition, data mining and machine learning systems are being developed to process complex data and predict problems (Gladju et al., 2022). Artificial neural networks (ANNs) have recently attracted much attention due to their wide range of applications and ability to solve complex problems. Correlated patterns between input data sets and associated target values can be found and learned by ANNs. Once trained, ANNs can be used to predict the output of new, independent input data. Even when the inputs are noisy and imprecise, ANNs can handle problems with highly complex and non-linear data by mimicking the learning process of the animal brain. This makes them ideal for modelling highly complex and often non-linear ecological data (Lek and Guégan, 1999).

Neural network algorithms are recognised as one of the most effective and widely applied types of artificial intelligence. In this context, a neural network refers to a set of computational nodes or artificial neurons and synapses that form a structure similar to the human brain. This type of network is usually trained to regenerate another function with input data (e.g. images) and output values or categories (e.g. classes). A neural network consists of an input layer of neurons equivalent to the input data and an output layer of neurons that represent the values or categories to be determined. There are often other layers between the input and output layers. These are called hidden layers. When a network contains multiple hidden layers, it is called a DL or DNN (Goodwin et al., 2022). Although the unique functioning of the human brain inspired the development of ANNs, the two are very different. While ANNs cannot mimic the complexity of the brain, they share two important characteristics with real neural networks. First, the underlying computational devices with a high degree of interconnectivity form the basis of both networks. Second, the way the neurons are connected determines how the network works. The human brain consists of about 8.6×10^{10} neurons, or computational elements. These neurons communicate with each other through a network of connections, with each unit having about 7000 synaptic connections (Park et al., 2016). A type of computational model inspired by the architecture and functioning of organic brain systems in animals is a neural network. They include very basic computing components known as neurons, which get signals from other parts of the system, analyze them using a particular function and then pass on the output. Neurons in a neural network are arranged in a layer fashion where every layer has a certain function to compute for. Most of the times, the layers are ordered, with the output layer giving the end result and the input layer getting the raw data (Saleh, et al., 2023). Based on the internal architecture, ANNs can be of different types such as radial basis network (RBN), learning vector quantization, neocognitron, feedforward neural networks with backpropagation algorithms and self-organising mapping (SOM) (Cabreira et al., 2009).

The importance of the marine environment and fish habitats is increasing due to the fact that they are a valuable source of food, and are also important in the implementation of measures that help conservation of fish species (Yáñez et al., 2010). The management of fisheries which incorporates biological, social and economic aspects of fish stock is used in meeting the food requirement of the population without overexploiting fish stock (FAO, 2003; Şahin et al., 2008; Jisr et al., 2018; Mutlu et al., 2018). As stated by Zargar et al. (2012), biometric studies which give information on the fish species to determine their biomass are very useful for research and management. In the next years, the management of sustainable fisheries technology will tackle on the improvement of piscimetry or the use of advanced modeling in the field of fisheries (Suryanarayana et al., 2008). Evolution in the automation and smart technologies have led the aquaculture to grow in intensity and intelligence. Due to these developments, the aquaculture environment has also transformed into a sustainable system that has enhanced the productivity of aquaculture (FAO, 2018; Avnimelech, 2009; Zhao et al., 2021).

The present AI strategies aim at improving resource utilization while policy support remains inadequate. Analysing government strategies for moulding technological change is as crucial as AI for sustainable fisheries (Honarmand Ebrahimi et al., 2021). The artificial neural networks are considered as an effective tool for stock assessment and fisheries management. In the future, the use of this technology will be increased and will help in the management of fish stock and the conservation of marine environment (Goodwin et al., 2022). There is research on different practical applications of data mining and machine learning in relation to aquaculture and fisheries.

1.2 The role of machine learning (ML) algorithms in application domains

Machine learning which is a branch of artificial intelligence, defines machine learning as the ability of a computer to learn from the data provided to it, auto identify patterns and make decisions. Traditional human activities are being gradually substituted by the increasing use of machine learning based non-invasive testing methods which are very useful in aquaculture (Hassoun et al., 2023). This is because the systems are capable of gathering high quality data easily without disrupting the growth of the fish (Li et al., 2020; An et al., 2021). The application of ML techniques has been increasingly used as a decision-making instrument in the management as well as protection of inland water resources (Isık and Akkan, 2024; Palabıyık and Akkan, 2024). Since there is a vast variety of machine learning models, it is crucial to perform a comparative analysis of such models as preliminary research for future modelling uses in order to enhance the comprehension of the potential of machine learning in ecology (Olaya-Marín et al., 2013).

Due to the capabilities of the modern techniques, machine learning methods are faster, effective more than accurate the and traditional more ones in analysis of big data (Ahmad, 2019; Isık et al., 2024). Machine learning is concerned with learning new knowledge, skill learning and knowledge updating. It covers the use of algorithms for data processing and understanding; models are defined by a large number of participants, potential benefits and flexibility to accommodate new data. Mathematical models are also applied to analyse and interpret data with a view of enhancing the performance of the information system (Zhao et al., 2021). Some of the machine learning techniques include principal component analysis, artificial neural networks, decision trees, and support vector machines that have been found to yield satisfactory results in underwater image processing (Zion, 2012). Numerous studies suggest that machine learning outperforms traditional parametric models in prediction because of its ability to handle complex and nonlinear interactions (Guisan and Zimmermann, 2000; Smoliński and Radtke, 2017).

One of the most common types of representation learning algorithms which are based on artificial neural networks is called deep learning which is a category of machine learning (Deng and Yu, 2014; Cansu et al., 2024). Especially, deep learning as a branch of machine learning can be employed for a number of applications for artificial intelligence, although not all (Goodfellow et al., 2016; Saufi et al., 2019; Yang et al., 2021a). The deep learning state that is in line with the shallow learning is that both of them are based on the feed-forward back propagation neural networks (Cui et al., 2020). Deep learning (DL) is a category of machine learning (ML) that is concerned with learning representations as opposed to task-specific algorithms. These are models that try to imitate the architecture and function of a human brain. The method allows a computer to gain knowledge from experience and is made of a hierarchy domain. of Since concepts the in data is collected automatically in this approach, there is no need for a human being to feed information into the computer (Abdolrasol et al., 2021).

In their place, traditional techniques have been substituted by deep learning (DL) and machine learning (ML) algorithms in those applications where state of the art detection technology is deployed, as they are low cost, easily implementable and require no manual effort. In aquaculture, the quality assessment methods have been enhanced with the use of imaging technologies and the application of deep learning techniques. For instance, SVM and ANN have been used to determine freshness of fish, for example, by Jayasundara et al. (2023). Application of DL techniques in fish identification is still in the initial stages, but has been on the rise in the recent past. A CNN was suggested by French et al. (2020) for fish counting in a video and the results were analyzed by Palmer et al. (2022).

In the past few years, several researchers have improved the fish detection and identification capabilities using machine learning and artificial intelligence techniques to analyze the variations in the fish stock in specific locations. The current most advanced type of machine learning is the deep learning which is extensively used in machine vision. Out of the different types of neural networks, convolutional neural networks (CNNs) have been observed to produce best results for image identification and filtering (Jiang et al., 2022).

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CHAPTER II:

ARTIFICIAL INTELLIGENCE APPLICATIONS: LENGTH-WEIGHT AND AGE OF FISH DETERMINATION

Buse Eraslan Akkan[1], Serap Eşkin[2], Cengiz Mutlu[3]

This chapter began with the identification of keywords that could be associated with fish biology and ecology when conducting a review of the literature. These keywords were chosen in order to capture a broad spectrum of the literature relevant to the study. The sources of information used in this chapter are Science Direct, Google Scholar, IEEE Xplore, Springer Link and Oxford Academic; these databases have been chosen to offer recent and credible databases in the field of aquaculture and fisheries.

Based on the identified keywords, a proper search strategy was designed in order to identify the articles that could be relevant to this chapter. While searching for the articles, the titles, the abstracts and the keywords of the articles were read. Certain criteria were defined for the inclusion of the reviewed articles and they included; the article should be timely and relevant to the subject matter in question, the article should be about fish biology or ecology and the article should employ machine learning or deep learning.

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The following exclusion criteria were set as irrelevant studies and duplicated studies. The articles were evaluated in relation to fish length, weight and age, and this information was compiled in tables. This was done in order to compare the practices and the efficiency of the methods used in different countries. A brief overview of the research is given in tables and the part to be covered, the method used and the result obtained is explained well in detail. This approach forms a strong platform for the assessment of the suitability of the application of deep learning and machine learning in hydrobiology, fisheries and aquaculture management.

2.1. Size of Fish

In the aquatic environments, it is imperative to know the size of fish for the purposes of fish biology, ecology as well as fisheries management. Fish size is a key factor which determines the prey-predator relationships, species composition and growth in the aquatic environments. It also has significant implications on the reproductive potential. This can provide important insights into population dynamics and ecosystem functioning (Ankitha et al., 2024). Inferring the overall health of communities by measuring the length of fish in sampled subsets of species and combining this information with other key ecosystem indicators is the basis for assessing the health of fish populations (Yazıcıoğlu and Akkan, 2022; Marrable et al., 2023). Traditionally, observers or fishermen on the boat measure the length of fish by hand. However, manual measurement is time-consuming and hinders fishermen's work. It is also common to doubt the accuracy of the information provided. An automated method for determining the body length of fish harvested on board vessels is needed to speed up the process and increase the accuracy of the data (Tseng et al., 2020). Traditional methods of collecting length and weight data involve physically touching the fish, which wastes staff time and stresses the fish. To guarantee precision and accuracy, measurements are often made in the field, where conditions may not always be ideal. The accuracy of measurements can be affected and vary for simple reasons such as wind, splashing of fish, or differences in staff measurement procedures (Gutreuter and Krzoska, 1994; Akkan et al., 2018). Recent advances in machine learning and imaging technologies are now replacing the collection of biometric information (Bravata et al., 2020; Yazıcı et al., 2024). The results of fish size determination studies conducted in different countries are presented in Table 1.

Table 1: Summary of studies on length and size estimation of fish species with neural networks in different countries

Country	Field of Application	Environment	Proposed Model	Other Compared Models	Year	Species of Studied	Method of Accuracy Measurement	Author	Journal
Argent	Estimation of Fish Lenght	Marine	Multilayer Perceptron (MLP) Artificial Neural Network	Single hidden layer artificial neural network	2015	*Engraulis anchoita*	Correct Classification Rate	Solari et al., 2015	IEEE/OES Acoustics in Underwater Geosciences Symposium
England	Estimation of Fish Length	From Online Public Resources	The three Regional Convolutional Neural Network (R-CNN) Models are: ResNet-101, Single shot MobileNet detector, and NASNet	Not Specified	2019	European sea bass - *Dicentrarchus labrax*	MAE, MBE	Monkman et al., 2019	Methods in Ecology and Evolution
USA	Estimation of Fish Length	Lake	Deep Convolutional Neural Networks (DCNN)	Ensemble	2020	22 Different Fish Species	MAE, MPAE, MBE	Bravata et al., 2020	Ecology and Evolution
Taiwan	Estimation of Fish Length	From the Decks of Ships and Fishing Harbor	Convolutional Neural Network (CNN)	VGG-16 and AlexNet	2020	Tuna, Swordfish and Shark	MAE, MARE	Tseng and others, 2020	Biosystems Engineering
Spain	Estimation of Fish Length	Auction Centers	Mask R-CNN(Deep Convolutional Network)	Conventional	2020	*Merluccius merluccius*	RMSD	Álvarez-Ellacuría et al., 2020	ICES Journal of Marine Science
Norway	Estimation of Fish Length	Norwegian Sea	Mask R-CNN (Deep Learning Based Algorithm)	Semi Global Matching and Block Matching.	2020	*Pollachius virens* *Micromesistius poutassou* *Sebastes* spp. *Scomber scombrus*	Intersection over Union (IoU) and IoU* metrics	Garcia et al., 2020	ICES Journal of Marine Science
Greece	Estimation of Fish Length	HCMR (Hellenic Centre For Marine Research) Farm	Convolutional Neural Network (CNN)	Conventional manual measurement methods	2021	*Sparus aurata* *Dicentrarchus labrax*	Average relative length error	Voskakis et al., 2021	OCEANS 2021
Spain	Average Fish Size Estimation	Mediterranean	Mask R-CNN (A deep learning based model)	Statıstıcs Models	2022	*Coryphaena hippurus*	Mean Average Precision, F1 Score, Precision, Recall, Root Mean Squared Deviation (RMSD)	Palmer et al., 2022	Fisheries Research
Spain	Estimation of Fish Length	Local Fish Markets	CatBoost Regression Model	Extremely Randomized Trees (ERT)	2022	Common Fish Species	MAE	Climent-Pérez et al., 2022	International workshop on soft computing models in industrial and environmental applications
İtaly	Estimation of Fish Length	Aquaculture Farm	Artificial İntelligence Algorithms	Conventional Manual Measurement Methods	2022	*Sparus aurata*	MAPE	Tonachella et al., 2022	Scientific Reports

South Korea	Fish Standard Length Distributions	Fresh Water Resources	(SOM) model	Shannon and Simpson Diversity İndices	2022	32 Fish Species	Not Specified	Yu et al., 2022	Fishes
Malaysıa	Estimation of Fish Length	Setiu Wetland	Random Forest	Multiple Linear, Lasso, Ridge, Decision Tree, XGBoost	2023	19 Fish Species	MAE, RMSE, R^2	Hassan et al., 2023	BIO Web of Conferences
Sri Lanka	Estimation of Fish Length	Marine	FishNET-S and FishNET-T	Not Specified	2023	*Sardinella longiceps Thunnus albacares*	Not Specified	Jayasundara and at. al., 2023	Journal of Agriculture and Food Research
Australia	Estimation of Fish Length	Ozfish Stereo-BRUVS Images	YOLOv5 (You Only Look Once) deep learning model	Conventional Measurement	2023	319 Different Fish Species	Pearson Correlation Coefficient, F1 Score, Sensitivity	Marrable et al., 2023	Frontiers in Marine Science
Japan	Estimation of Fish Length	Odawara Fishing Port	Mask R-CNN (Mask Region-based Convolutional Neural Network)	Not Specified	2024	85 Species of Fish	Mean Average Precision - mAP	Iwahara et al., 2024	bioRxiv
Türkiye	Heihgt-Mass Estimation	Lake of Munzur	Neural Network Toolbox, , “back propagation”	Not Specified	2024	*Alburnus sellal*	MAPE	Ozcan, 2024	Oceanological and Hydrobiological Studies
China	Estimation of Fish Length	Marine	CatBoost regression model	PSPNet, UNet and DeepLabV3+	2024	*Epinephelus lanceolatus*	Pixel Accuracy (PA), Intersection over Union (IoU), Mean Intersection over Union (MIoU), mean absolute error (MAE), root mean square error (RMSE) and coefficient of determination (R^2)	Cong et al., 2024	Aquaculture International
Brazil	Estimation of Fish Length	Freshwater Fish	Mask R-CNN Model	Not Specified	2024	Babão, Bodó, Caparari, Cará, Coroatá, Curimba, Dourada, Filhote, Jaraqui, Jaú, Pacu, Pescada, Piau, Piranha, Pirarara, Sardinha, Surubim, Tambaqui, Traíra, Tucunaré, Peixe Zebra	Intersection over Union (IOU) metric	Rocha et al., 2024	Multimedia Tools and Applications
Türkiye	Estimation of Condition Factor (CF), Length, Weight and Gender Relationship	Marine	Multilayer Perceptron Artificial Neural Network (MLP-ANN))	Support Vector Machine (SVM), Neural Network/ Multilayer Perceptron (MLP), Ensemble Learning, Gaussian Process Regression (GSR), Decision Tree and Linear Regression	2024	*Nemipterus randalli*	RMSE, MAPE ve R^2	Akkan et al., 2024	Acta Biologica Turcica

Table 1 provides a comprehensive summary of fish length determination studies carried out in different countries and in various environments. In general, the diversity of the studies and the fact that they were carried out on different fish species in various countries shows the international dimension of research in fisheries and marine biology. Among the models used, deep learning methods (DCNN, Mask R-CNN, CNN, YOLOv5) are frequently preferred, while traditional methods (Multiple Linear, Lasso, Ridge, etc.) are also used in some studies; this situation reveals the importance of hybrid approaches. The use of different accuracy measurement methods (MAE, RMSE, mAP, IoU, etc.) shows that the models offer a wide range to compare their performance.

When analyzed on a year-by-year basis, more studies have been conducted and applications of deep learning techniques have increased in the post-2020 period; this is a result of technological advancements and increased data processing capabilities. When analyzed by country, the fact that the U.S. and Australia strive for high accuracy using advanced deep learning models reflects the wealth of technological infrastructure and research resources in these countries. In Türkiye, studies of local species using the Neural Network Toolbox are making an important contribution to the conservation of local ecosystems. Spain has set the trend in this regard and has conducted several researches and has worked on numerous species and models. The works done in South Korea and Brazil on some less known species offer a different view on the fisheries research in these countries.

2.2. Weight of Fish

Fish biomass is one of the most effective indicators that can help to understand the state of fish and the environment (Abinaya et al., 2022). This chapter focuses on the use of fish biomass since the aquaculture and fisheries sectors depend on it (Li et al., 2020). It is commonly used in fisheries to determine the feeding rates and it also provides useful information on the diet of the fish. It is also applied during harvest to establish the market value, size of maturity and quality of the fish (Liu et al., 2019). By using the fish biomass data, the aquaculture businesses can optimize the plant investments and also can deal with the water quality problem due to over feeding. Most of the scientific management and conservation measures of fisheries resources for sustainable fish production are based on the quantitative assessments of fish biomass. Therefore, it is imperative that the biomass of fish is accurately measured by the aquaculturists.

The impacts of human interventions on aquatic environments can be evaluated while the impacts of management actions can be evaluated and fishery management and conservation measures can be enhanced with this information (Cochrane, 2002; Rani et. al., 2024). Length-weight relationships or LWRs present important growth information when used in case studies pertaining to the determination of certain biological parameters including age, maturity and nutrition (Froese, 2006; Sonwal et. al., 2022).

Ecology, population assessment, trophic interactions in ecosystems, biodiversity studies, ecosystem modeling, habitat assessment, climate change research, and sustainable fisheries management all rely heavily on the estimation of fish weights. Fish need a lot of time, effort and stress when using human measurement methods, so it is important to create fast and reliable indirect measurement approaches such as machine learning (Hassan et al., 2023). The results of fish weight determination studies conducted in different countries are presented in Table 2

Table 2: The results of fish weight determination studies conducted in different countries

Country	Field Of Application	The Environment	Proposed Model	Other Compared Models	Year	Species of Studies	Method of Accuracy Measurement
Italy	Weight of Fish	Various Farms (especially trout)	Support Vector Machines (SVM)	Traditional Methods	2000	Trout	Not Specified
Türkiye	Weight of Fish	Trout Farm	Linear, Power, Second Order Polynomial Regression	Not Specified	2010	*Oncorhynchus mykiss*	R^2
Iran	Weight of Fish	From Fish Farm	Linear and Multiple Regressions	Not Specified	2016	*Oncorhynchus mykiss*	R^2, regressiont-testi, R^2adj, SEE, F-test and variance inflation factor (VIF)
Australıa	Weight of Fish	Farm Environment or Natural Habitats	Two Different Deep Learning Approaches; LinkNet-34 and LinkNet-34R network	Mathematical Models	2019	Asian Sea Bass	MAPE
Türkiye	Weight of Fish	Lake of Murat (Palu-Elazığ)	Network Toolbox of MATLAB. MLP - Multi-Layer Perceptron	Not Specified	2019	*Alburnus mossulensis*	MAPE
Brazil	Weight of Fish	Aquaculture Laboratory (Laqua)	Deep Learning based computer vision system (CVS)	Traditional Image Analysis Methods (e.g., IMAFISH)	2020	*Oreochromis niloticus*	R^2
Türkiye	Weight of Fish	İskenderun Gulf	M5P (nonlinear regression) algoritması	Artificial Neural Network(MLP - Multi-Layer Perceptron) LR - Linear Regression	2020	*Sparus aurata*	(CC-correlation coefficient, MAE-mean absolute error, RMSE-root mean squared error, RAE-relative absolute error, RRSE-root relative squared error)
China	Weight of Fish	Pool	PCA-CF (Principal Component Analysis - Calibration Factor) and BPNN (Back Propagation Neural Network))	BPNN-Weight, SVR-Weight (Support Vector Regression), LDA-CF-BPNN (Linear Discriminant Analysis), PCA-CF-DT (Decision Trees), PCA-CF-KNN (k-Nearest Neighbor), Length-Weight, Area-Weight and Multifactor Weight.	2020	Pond Fish (*Crucian carp*)	MAE, R^2 and RMSE

Fınland	Weight of Fish	Lake Längelmavesi	Genetic Programming (GP) based symbolic regression	Linear Regression, Power Function, k-Nearest Neighbor (KNN), Ridge Regression, Decision Tree, Random Forest, Gradient Boosting, Multilayer Perceptron	2021	Perch Bream Roach Pike	R^2, MSE, RMSE and MAE
New Zealand	Weight of Fish	Nelson Research Center	DenseNet-121	VGG-11, ResNet-18	2021	*Chrysophrys auratus*	R^2, MSE and RMSE
Sweden	Weight of Fish	Obtained from Images Collected During Fishing Operations on Vessels.	β-Variational Autoencoder (VAE), Support Vector Regression (SVR) for weight estimates	Not Specified	2021	Cod, Pollock and Haddock	MAPE and RMSE
Thailand	Weight of Fish	From Bioflock Tanks	"TWE-DRL" (Tilapia Weight Estimation - Deep Regression Learning)	Linear Regression (LR), Random Forest Regression (RFR) and Support Vector Regression (SVR)	2022	*Oreochromis niloticus*	MAE and R^2
Malaysia	Weight of Fish	Setiu Wetland	Random Forest	Multiple Linear Regression, Lasso, Ridge, Decision Tree, XGBoost	2023	19 Fish Families	R^2, RMSE and MAE
Mexico	Weight of Fish	Pool ve Aquarium	Multilayer Perceptron	Linear Regression (LR) Power Model (PM)	2024	*Oreochromis niloticus*	MAE and R^2
Türkiye	Weight of Fish	Lake of Munzur	Neural Network Toolbox, ,"back propagation"	Not Specifies	2024	*Alburnus sellal*	MAPE

The studies presented in Table 2 detail the studies and methods used for biomass calculations in different countries. The field of application broadly focuses on biomass, despite the representation of various countries such as Iran, Australia, Mexico, Thailand, Türkiye, Finland, Brazil, Malaysia, New Zealand, Sweden, China, and Italy. The studies focus on information from different data sources, such as fish farms, natural habitats, ponds, laboratory conditions, and water areas. Statistical measures such as R^2, MAE, RMSE were used as accuracy measurement methods. These methods are critical for assessing the reliability of research results. The models proposed in the table include classical regression approaches as well as machine learning-based methods. For example, modern techniques such as deep learning, support vector machines and genetic programming have been used in studies in several countries. Some studies have chosen to combine both classical and modern methods. In this context, the fish species studied include different species such as trout, sea bass, tilapia and sea bream, which increases the diversity and scope of the applications.

Different countries use various methods to estimate the biomass (mass) of fish. These methods include statistical and machine learning techniques such as linear regression, artificial neural networks, deep learning and genetic programming. The studies have been carried out on different fish species living on farms, in natural environments and even in aquariums. The results have important applications in areas such as fisheries management, aquaculture and ecosystem analysis. Notable deep learning models have become increasingly prevalent in this field in recent years. Studies in Türkiye have mainly focused on native species such as trout, while in China, they have focused on specific species such as pond fish, whereas researchers are studying a wider variety of fish species in European countries. In the future, researchers can obtain more accurate and reliable predictions by combining different models, using large data sets, and integrating physical and biological information.

In conclusion, from the table, it is evident that research on fish culture and management is vast and diverse across the different countries and the techniques used. The integration of deep learning and regression techniques enhance the accuracy of the fish weight prediction models. The findings from these studies help in providing important information to be used in fisheries management and sustainable fisheries practices.

2.3. Age Determination of Fish

All around the world, governments are making huge efforts to get fish ages that are necessary for the fisheries management programs (Hilborn and Walters, 1992). Age of fish is one of the most important biological parameters that characterizes the life history (growth and maturity ages) and dynamics of fish stocks (Hilborn et al., 2013; Ma et al., 2024). Age of fish is a critical element that helps in assessing the health of the fish stocks and also in determining the measures that need to be taken for the management of the fish stocks so as to ensure their sustainability. The most common estimation applied to fish otolith age images is visual approximation analysis, but this can be quite costly and labour-intensive (Politikos et al., 2021). There is a need to develop cheaper and efficient methods that can accurately determine the age of fish (İşgüzar et al., 2024).

The application of Artificial Neural Networks (ANNs) presents an opportunity to automate the normal fish aging process as it is faster, objective and consistent and also capable of outputting measures of uncertainty in the age estimation. ANN models were tested in order to ascertain the ability of the model to reproduce the age estimates of an experienced human reader (Robertson and Morison, 1999). One of the main techniques used today for fish age discrimination is the automatic interpretation and recognition of fish age using otolith pictures (Bermejo et. al, 2007). Regarding the use of artificial intelligence and statistical learning in determining the age of fish, Robertson and Morison (1999) aimed to reduce subjective errors with artificial neural networks; while the results were similar in some species, error rates were high in others. Fablet and Le Josse (2005) analyzed plaice otoliths and obtained 88% agreement. Engelhard and Heino (2004) modeled the age at maturity of Norwegian herring and showed that stock abundance affects maturity. Furthermore, machine learning is required for age estimation using otolith images and has been effectively used in comparable image analysis tasks such as object identification (Moen et al., 2018). Deep learning was used to automatically analyze otolith images using transfer learning to apply the pre-trained parameters of ImageNet to the trained CNN model to determine the age of the fish (Zhao et. al., 2021). The results of fish age determination studies conducted in different countries are presented in Table 3.

Table 3: Summary of studies on age detection estimation of fish species with neural networks in different countries

Coutry	Field of Applica-tion	Area	Proposed Model	Other Compared Models	Year	Type Worked	Method of Accurac-y Measurement	The Author	Journal
Australia	Age	Marine	Probabilistic Neural Network	Back Propagation Neural Network and Multiple Hidden Layer Neural Network)	2001	King George Whiting, Ling, Snapper, Black Bream, School Whiting, Blue Grenadier, Ocean Perch, Sand Flathead, Pilchard	Average Percent Error - APE	Robertson and Morison, 2001	Book
England and France	Age	Marine	Kernel Logistic Regression (Klr) and Support Vector Machines (Svm)	Unspecified	2006	*Pleuronectes platessa*	Not specified	Fablet, 2006	Fisheries Research
Norway	Age	Sea of Barents	Deep Learning Based Convolutional Neural Networks (Cnn)	Elliptic Fourier Descriptors (Efd)	2021	Northeast Arctic Cod (Neac) Norwegian Coast Cod (Ncc) Greenland Flounder	MSE	Martinsen, 2021	Master's thesis
Greece	Age	Aegean Sea and Ionian Sea, Greece	Deep Learning Based "Fish Age Network (Fan)" And "Fish Age-Longevity Multitask Network (Faln)" Enhanced by Multitask Learning	Not Specified	2021	*Mullus barbatus*	MSE	Politikos et al., 2021	Fisheries Research
Türkiye	Age	Lake of Mogan (Türkiye)	J48 Decision Tree (J48 Dt) and Random Forest (Rf) Algorithms	Naive Bayes (Nb) and Artificial Neural Networks (ANN)	2022	*Tinca tinca*	Accuracy (%), Precision, Recall	Benzer et al., 2022	Fisheries Research
Norway	Age	Norwegian Institute for Marine Research	A Convolutional Neural Network (CNN) Based Model (Xception Architecture)		2022	*Reinhardtius hippoglossoides*	Coefficient of Variation (CV), RMSE	Martinsen et al., 2022	PLoS One
İceland	Age	İceland Marine and Freshwater	A Low Instance Learning Approach Using the CLIP Image Coder (CLIP Regression Model)	Vit (Vision Transformer), Resnet-50	2023	*Pleuronectes platessa* *Gadus morhua* *Reinhardtius hippoglossoides* *Melanogrammus aeglefinus*	Classification accuracy (Accuracy) Precision Recall F1 score RMSE	Sigurðardóttir et al., 2023	Ecological Informatics
USA	Age	From the eastern Bering Sea	Deep Learning Based Multimodal Convolutional Neural Network (Mmcnn)	Least Squares Regression (Pls) Model	2023	*Gadus chalcogrammus*	R^2 RMSE	Benson et al., 2023	Canadian Journal of Fisheries and Aquatic Sciences
Taiwan	Age	Offshore	Otolith Mass Estimation and Image Augmentation (OMIA) Model	Not Specified	2024	*Thunnus orientalis*	R^2, Coefficient of variation (CV)	Ma et al., 2024	Fisheries Research
Japan	Age	Estuaries and Rivers	A Hybrid Deep Learning System; Yolov5 Object Detection Model and Pspnet	Not Specified	2024	*Oncorhynchus keta*	MAE Precision Accuracy	Vasumathi et al., 2024	International Conference on Science Technology Engineering and Management
USA	Age	Gathered from Surveys and Local Fishermen	Auto correlation Integrated Moving Average	Not Specified	2024	*Micropogonias undulatus* *Helicolenus dactylopterus*	Akaike Information Criterion (AIC) MSE	Kirch, 2024	Doctor of Philosophy (PhD) thesis
USA	Age	Gulf of Alaska (Goa) and Aleutian Islands (Ai)	Fourier Transform Near Infrared (Ft-NIR) Spectroscopy Coupled with Multimodal Convolutional Neural Networks (Mmcnn)	Traditional Microscope Based Age Estimation Method	2024	*Sebastes polyspinis*	R^2 RMSE RPD CV	Benson et al., 2024	Fisheries Research

Table 3 provides a comprehensive summary of fish age determination studies carried out in different countries and in a variety of settings. These studies from different countries (Taiwan, Türkiye, Norway, the UK, France, Greece, Australia, Japan, the USA, and Iceland) are indicative of the growing interest in fish age estimation on a global scale. Researchers have conducted most of the studies in marine and freshwater environments, underscoring the significance of fish age estimation for ecosystem health and management. More sophisticated and deep learning-based models, such as CNN and YOLOv5, have gained prominence in recent years. This illustrates the application of technological advances in research.

Each study proposes a specific model, examines its effectiveness, and compares it with other models. For example, the OMIA model has been proposed in Taiwan and the J48 DT and RF algorithms in Türkiye. Studies on similar species in different countries provide an opportunity to compare the effectiveness of various models and thus understand which approach yields better results. Furthermore, the various authors have employed different statistical measures such as R^2, RMSE, and MAE to assess the precision of their models which enhances the comparability of the findings (Cansu et al., 2024; Isık and Akkan, 2024; Palabıyık and Akkan, 2024).

The research has been done in different marine and lake environments and on different species of fish. For instance, understanding the species like Pacific bluefin tuna, Northeast Arctic cod and red mullet helps in better understanding of ecosystems and fisheries productivity. Additionally, the impact of technologies developing over time is also observed; the increase in deep learning techniques, especially in recent years, shows that research in this field has become more modern.

In the 2024 studies, efforts to achieve precise results in fish age estimation using a wide range of advanced algorithms are prominent. Differences between countries vary depending on local fishing practices, ecosystem structures, and existing technological infrastructures. This illustrates how local and cultural influences shape research topics.

2.4. Abundance of Fish

The amount of fish in a shoal can be a useful indicator for the creation of intelligent production management systems in intensive aquaculture. However, the traditional artificial sampling procedure can be tedious and time-consuming, as well as stressful for the fish (Zhang et. al., 2020).

Sustainable management of fisheries depends on reliable fish stock assessments. However, especially in ecosystems changing due to global warming and other anthropogenic stresses, the effectiveness of current statistical stock assessment models in predicting critical stock metrics such as recruitment or spawning stock biomass may be poor (Lüdtke and Pierce, 2023).

Fish abundance depends on a number of factors, such as egg dynamics, fry recruitment, distribution, developmental stages, biomass availability, mortality due to predator consumption, the closure of fishing grounds, unorganized fishing, and catastrophic events (Suryanarayana et al., 2008).

Nonparametric machine learning models, including Gaussian Process Models (GPR) (Munoz et. al., 2013), ensemble regression (ER) (Guo et. al., 2015), and artificial neural networks (ANNs) (Cohen and Wallén, 1980; Zhang et al., 2008; Tuhtan et al., 2017), have been used to estimate fish densities, as machine learning techniques can give more accurate predictions than parametric models. Researchers have estimated fish distributions using a variety of models, but many studies have relied on a single parametric or nonparametric model, which is inadequate (Do and Tran, 2023). The results of fish abundance determination studies conducted in different countries are presented in Table 4.

Table 4: Summary of studies on fish species abundance prediction with neural networks in different countries

Country	Field of Application	The Environment	Proposed Model	Other Compared Models	Year	Type Studied	Method of Accuracy Measurement	The Author	Journal
USA	Estimation of Salmon Production	Lake of Ontario	Artificial Neural Networks	Traditional Statistical Methods	2005	Salmon Fish	MSE and R^2	McKenna, 2005	Transactions of the American Fisheries Society
Chile	Estimation of Fish Abundance	Marine	An Artificial Neural Network (ANN) model calibrated with the Levenberg-Marquardt algorithm	Not Specified	2010	Anchovy Fish (*Engraulis ringens*) and Pacific Sardines (*Sardinops sagax*)	R^2	Yáñez et al., 2010	Progress in Oceanography
Mexico	Estimate of Fish Catch	Marine	NARNN) and LSTM)	Not Specified	2018	Paralabrax Nebulifer and Caulolatilus Princeps	R^2 and MSE	Cavieses Núñez et al., 2018	Journal of Marine Science
China	Estimated Number of Fish Population	Yellow Sea	Hybrid deep neural network model, multi-column convolutional neural network (MCNN) and extended convolutional neural network (DCNN)	Traditional Machine Learning Based, Methods, Linear Regression, Random Forest,Gradient Boosting	2020	Atlantic Salmon (*Salmo salar*)	Not Specified	Zhang et al., 2020b	Animals
Malaysia	Marine Fish and Aquaculture Forecast	Both Marine and Fresh Water	VR technique created by combining different machine learning models		2021	Not Specified	R^2 MAPE MAE PBIAS (Bias Percentage)	Rahman et al., 2021	Sustainability
Germany	Estimated of Fish Abundance	Baltic Sea, North Sea and from North Atlantic	An approach combining the stock assessment model (SAM) and the gradient boosted tree (GBT) model	Not Specified	2023	Western Baltic Cod (*Gadus morhua*) North Sea Whiting (*Merlangius merlangus*) Plaice (*Pleuronectes platessa*) Ling (*Molva molva*) Norwegian And Barents Sea (*Gadus morhua*)	RMSE and R^2	Lüdtke and Pierce, 2023	arXiv preprint arXiv: 2308.03403
Indonesia	Estimated of Fish Production	From the Seas of Indonesia	Time Series Analysis (such as ARIMA, SARIMA) or Machine Learning models (Random Forest)	Not Specified	2023	Species of High Economic Value	Not Specified	Pradana, 2023	JISA (Jurnal Informatika dan Sains)
Northern Chile	Estimated of Fish Abundance	Marine	GARCH-X (Generalized Autoregressive Conditional Heteroskedasticity) model	Gaussian Assumed GARCH-X Models	2024	Anchovy Fish (*Engraulis ringens*) and Pasific Sardines (*Sardinops sagax*)	MAE, MSE and R^2	Plaza-Vega et al., 2024	Progress in Oceanography
Bangladesh	Estimated of Fish Production	Bangladesh Bureau of Statistics	Hybrid model (combination of ARIMA and ANN)	ARIMA (Autocorrelation Integrated Moving Average) and Artificial Neural Network (ANN) Models	2024	Not Specified	MAE MAPE RMSE	Saif and Khanam, 2024	Dhaka University Journal of Science

Table 4 presents a comparative overview of various statistical and machine learning models used to predict fish populations in different countries and seas. The studies have been carried out in various countries such as Northern Chile, Chile, Germany, China, Bangladesh, Mexico, Indonesia, Malaysia, and the USA. Most studies focus on the marine environment and emphasize the management of marine ecosystems. Studies have generally focused on fish species with high economic value, such as anchovy, sardine and salmon. Depending on the size and complexity of the data set, we preferred statistical models (GARCH-X, ARIMA) or machine learning models (artificial neural networks, random forests) for model selection. Model performance was evaluated with metrics such as R^2, MSE, and MAE. The studies provide important data for developing fisheries management policies and ensuring sustainable fisheries. Furthermore, the use of machine learning and deep learning methods increases data analysis and prediction capabilities in fisheries. This table constitutes an important resource for fisheries management and environmental sustainability.

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CHAPTER III:

ARTIFICIAL INTELLIGENCE APPLICATIONS: FISH SPECIES IDENTIFICATION

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This chapter began with a systematic review of the current literature and the identification of keywords related to species determination and abundance determination. These keywords were chosen to encompass a wide range of relevant studies in the literature. Electronic databases used in the chapter include Science Direct, Google Scholar, IEEE Xplore, Springer Link, and Oxford Academic; these databases were selected to provide up-to-date and authoritative resources in the field of aquaculture and fisheries.

Using the keywords identified, a detailed search strategy was developed to find related articles. During the search, the titles, abstracts and keywords of the articles were used. Specific criteria were set for the inclusion of the reviewed articles, which included having current and relevant content, being related to identification of fish species, and including machine learning or deep learning methods.

Exclusion criteria were determined as irrelevant studies and repetitive studies. This analysis was carried out to compare practices and the efficiency of methods in different countries.

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Tables summarize the research, presenting the scope of each study, the methods used, and the results obtained in detail.

3.1. Identification of fish species

Recognizing and identifying different fish species is essential for the fishing industry. Monitoring fish activities and determining the distribution of a given species are essential for the identification of endangered species, and accurate and reliable species classification and identification are essential components of these processes. This is also essential for managing and regulating the entire ecosystem, as well as for regulating production (Alaba et al., 2023).

Fish identification and categorization is a formidable task with potential for future research. It suggests that state-of-the-art technology, deep learning techniques, and artificial intelligence can simplify the process of identifying fish species (Rachmatullah et al., 2018; Hridayami et al., 2019; Monteiro et al., 2023).

Aquaculture has widely used deep learning (DL)-based object recognition approaches due to advances in machine vision and DL techniques. These algorithms have the advantage of simultaneously categorizing and localizing fish of interest in images (Liu et al., 2023). Since comparable species typically share many traits, it is difficult to differentiate between different species (dos Santos et al., 2019).

Fish species recognition is an area of research interest for machine learning and computer vision research, as it is a multiclass classification topic. Researchers apply the most developed algorithms to individual input images, primarily performing classification through the extraction and matching of shape and texture features. This information is based on studies conducted by Nagashima and Ishimatsu in 1998, Spampinato et al., in 2010, and Rathi et al., in 2017. The results of fish species identification studies conducted in different countries are presented in Table 1.

Table 1: Summary of studies on fish species detection predictions using neural networks in different countries

Country	Area of application	Environment	Proposed Model	Other Compared Models	Year	Type of study	Accuracy Measurement	Writer	Journal
Greece	Species Identification	Thermaikos Gulf	ANN	Not specified	1996	*Sardina pilchardus Engraulis encrasicolus Trachurus trachurus*	MSE	Haralabous and Georgakarakos, 1996	ICES Journal of Marine Science
Argentina	Species Identification	Sea	Artificial Neural Networks (ANN)	Feed Forward Neural Networks (FF) Using Back Propagation Algorithm Radial Basis Networks (RBN) Self Organizing Maps (SOM)	2009	*Engraulis anchoita Trachurus lathami Sprattus fuegensis Macruronus magellanicus Micromesistius australis Engraulis anchoita*	Not specified	Cabreira et al., 2009	ICES Journal of Marine Science
Japan	Species Identification	From Fish Markets	Layered Artificial Neural Network	Connected Neural Network	2009	11 Types of Fish	Accuracy Rate and Error Rate	Morimoto et al., 2009	J. Nat. Fish. Univ
Chile	Species Identification	Sea	Support Vector Machines (SVM)	MLP, ANN	2010	Sardine, Anchovy, Mackerel	Classification Accuracy	Robotham et al., 2010	Fisheries Research
Spain	Species Identification	Mediterranean Rivers	ANN	Random Forests (RF)	2013	Native Fish Species	R^2 MSE R^2Adj	Olaya-Marin et al., 2013	Knowledge and Management of Aquatic Ecosystems
Chinese	Species Identification	Fishnet River	Multi-Core Support Vector Machine (LS-SVM) with Bee Colony Optimization	Back Propagation (BP) Neural Network Method and Single Kernel LS-SVM	2014	Sea Bream, Cattle Fish, Pond Fish, Grass Carp Black Carp	Not specified	Wu et al., 2014	Transactions of the Chinese Society of Agricultural Engineering
India	Species Identification	From Underwater Observation Stations	Hybrid Convolutional Neural Network (CNN)	CNN Based Methods	2019	23 Different Types of Fish	Accuracy, Precision, Recall and F-Score	Deep and Dash, 2019	In 2019 6th International Conference on Signal Processing and Integrated Networks
USA	Species Identification	From Open Images Database	Regnety-16GF Based Model	Not specified	2022	10 Different Types of Fish	Not specified	Mujtaba and Mahapatra, 2022	International Conference on Computational Science and Computational Intelligence
South Korea	Species Identification	Rivers	Ensemble Artificial Neural Network (EANN	Support Vector Machines (SVM))	2022	Fish Communities (Especially Local Fish Species)	Nash–Sutcliffe Efficiency (NASH) Relative Root Mean Square Error (Rrmse) Relative Mean Deviation (Rbias)	Kang et al., 2022	Ecological Indicators
India	Species Identification	Obtained from Underwater Images	YOLO (You Only Look Once) and SE-Net (Squeeze-And-Excitation Network)	Various Deep Learning Based Approaches and Traditional Methods	2023	Sea Bream, Trout, Red Sea Bream, Red Mullet, Sea Bass, Striped Red Mullet, Shrimp, Horse Mackerel and Black Sea Sprat	Not specified	Dharshana veark., 2023	ICEEICT, 2023
India	Species Identification	From Various Parts of India	Convolutional Neural Networks (CNN) and Random Forest Classifier	VGG16 Based CNN Resnet50 Based CNN	2023	31 Different Types of Fish	Accuracy, Precision, Recall and F1 Score	Roy et al., 2023	International Journal of Computer Sciences and Engineering
South Korea	Species	From the fishermen	FD_Net	YOLOv3, YOLOv3-TL, YOLOv3-BL, YOLOv4, YOLOv5, Faster-RCNN ve YOLOv7.	2023	Gilt-head bream, Red sea bream, Red mullet, Horse mackerel, Black sea sprat, Striped red mullet, Trout, Shrimp	Intersection over Union (IoU) Generalized Intersection over Union (GIoU), Mean Average Precision (mAP), Hassasiyet (Precision) Duyarlılık (Recall), F1 Skoru	Malik et al., 2023	Plos one
Japan	Species	Ready Data Set Used	Transferable Fish Identification (TFI) Model	ResNet50 and Swin Transformer	2024	192 fish species	Micro F1-Score	Hasegawa et al., 2024	Journal of Marine Science and Engineering

Table 1 provides a broad overview of fish species identification studies carried out in different countries and in various environments. The common feature of these studies is the use of various machine learning methods to accurately and quickly identify fish species. Artificial neural networks (ANNs) and support vector machines (SVM) are the most widely used approaches in this field. The studies have been conducted in geographies as diverse as Saudi Arabia, Chile, Greece, Spain, Argentina, Japan, China, the US, India, and South Korea, indicating that the topic is of global interest. Moreover, the variability of the accuracy measurement methods (RMSE, MSE, precision, and F1 scores) is important to assess the reliability of the results. The studies were conducted over a period from 1996 to 2023, indicating that research has evolved in parallel with technological progress.

The focus on different fish species reflects diversity in fisheries and ecosystem research, while the use of diverse data sources, such as underwater images, wildlife museums, and fish markets, highlights the importance of diversifying data collection and analysis methods. In this context, elaboration of the study results may contribute to an in-depth examination of the issue.

The results of the studies show that deep learning techniques, especially convolutional neural networks (CNNs), are highly accurate in fish species detection. However, the success of the model directly depends on the quality and size of the data set used. The fact that data obtained from different environments has different characteristics affects model selection and performance. Therefore, it may be necessary to develop models specifically designed for each environment. Suggestions for future studies include using larger and more diverse data sets, combining different modalities, using transfer learning techniques, and developing interpretable models. In this way, it will be possible to make fish species detection models more accurate, faster, and more reliable. In summary, studies in the field of fish species identification show that this issue is both scientifically and commercially important. Thanks to emerging technologies such as deep learning, fish species identification will become even more automated and will make a significant contribution in areas such as aquaculture management, fisheries, and biodiversity conservation.

3.2. Classification of fish species

Accurate species categorization, identification, and enumeration are essential to managing and scientifically developing the fisheries sector, regulating fish reproductive density, and monitoring fish welfare. Science-based feeding and health care for fish are based on behavioral observation (Yang et al., 2021b). Species classification aids in identifying unwanted or invasive species, enabling the implementation of appropriate management actions (Zhang et al., 2016).

Identification of fish species can be useful for post-fishing audits because many countries have lists of protected species that are prohibited from fishing, and vessels may have fishing quotas that must not be exceeded. Creating sustainable and profitable fisheries also requires more economical and efficient monitoring of fish harvests, which often depends on accurately identifying and counting the various species (Ovalle et al., 2022).

The rapid advancement of machine learning and deep learning-based object recognition algorithms, which facilitate the rapid classification and localization of key fish features from photographs, has made aquaculture control selections more accurate (Liu et al., 2023). Morphologically based classification of fish species is error-prone and time-consuming. Accurate classification is important for yield estimation, production management, and ecosystem monitoring. Methods such as deep learning and transfer learning are being used to improve the fish classification process (Li and Du, 2022).

To achieve optimal performance, most research in the field of fish species classification has only applied or combined specific features and classifiers. Low-level and high-level features have never been used in any survey to categorize fish species, neither in the traditional method nor in the CNN-based technique. Optimal performance is guaranteed when these two features are used (Prasetyo et al., 2022). The results of fish species classification studies conducted in different countries are presented in Table 2.

Table 2: Summary of studies on fish species classification prediction with neural networks in different countries

Country	Area of application	Environment	Proposed Model	Other Compared Models	Year	Type of study	Accuracy Measurement	Writer	Journal
Mediterranean rivers	Fish Species Classification	River	ANN	RF	2013	Not specified	R^2, MSE and R^2Adj	Olaya-Marín et al., 2013	Knowledge and Management of Aquatic Ecosystems,
Nigeria	Fish Species Classification	Sea	Support Vector Machines (SVM)	Artificial Neural Networks (ANN), K-Nearest Neighbors (KNN), K-Means Clustering (K-Means Clustering)	2015	*Ethmalosa fimbriata Scomberomorus tritor*	Not specified	Ogunlana et al., 2015	African Journal of Computing & ICT
Chinese	Fish Species Classification	Sea	DeepFish	LDA + SVM, Raw-pixel SVM, Softmax Classifier	2016	23 Different Types of Fish	Accuracy (%)	Qin et al., 2016	Neurocomputing
Global	Fish Species Classification	Taiwan Coral Reefs	Deep Convolutional Neural Network (CNN).	Nearest Neighbor (KNN), Support Vector Machines (SVM), Sparse Representation-based Classification (SRC), PCA-KNN and PCA-SVM	2016	25 Different Fish Species	Average Count (Ac), Average Precision (Ap), Average Recall (Ar).	Salman et al., 2016	Limnology and Oceanography
Australia	Fish Species Classification	Underwater	A model based on deep convolutional neural networks (CNN)	HOG (Histogram of Oriented Gradients) + SVM (Support Vector Machine)	2017	Various Fish	Accuracy, Precision, Recall and F1 Score	Moniruzzaman et al., 2017	Springer International Publishing.
ABD	Fish Species Classification	Fish Images from the Sea and Fishing Nets	Deep learning	SSD (Single Shot MultiBox Detector) ve YOLOv2 (You Only Look Once)	2017	Lbacore Tuna, Bigeye Tuna, Dolphinfish, Opah, Shark, Yellowfin Tuna, Others	Cross-Entropy Loss	Chen et al., 2017	ICTAI
Global	Fish Species Classification	Aquarium and River	OFDNet	Not specified	2018	Herring, Mackerel	Average Sensitivity (mAP)	Christensen et al., 2018	Autonomous Underwater Vehicle Workshop
France	How Fish Can Be Classified According to Their Diets	Fresh Water	Support Vector Machine (SVM)	Random Forest (RF), Logistic Regression (LR), k-Nearest Neighbors (k-NN)	2018	*Oncorhynchus mykiss*	Correct Classification Rate (Ccr), Cohen's Kappa Coefficient, Sensitivity	Saberioon et al., 2018	Sensors
Indonesia	Fish Species Classification	Collected by searching species names on the Internet	FishNet	AlexNet	2018	*Katsuwonus pelamis Euthynnus affinis Coryphaena hippurus*	Not specified	Liawatimena et al., 2018	INAPR
Philippines	Fish Species Classification	Verde Island Passage	VGG16 deep convolutional neural network (DCNN)	lexNet	2019	*Amphiprion clarkii Chaetodon baronessa Ctenochaetus binotatus*	Accuracy Precision Recall F1 Score	Montalbo et al., 2019	International Conference on System Engineering and Technology
Taiwan	Fish Species Classification	Sea	GMM-YOLO	Traditional Computer Vision Techniques	2020	15 Different Fish	Not specified	Jalal et al., 2020	Ecological Informatics

Chinese	Classification of Fish Taxonomy	From Genbank Database	ESK (Elastic Net-Stacked Autoencoder) modeli	OC-SVM (One-Class Support Vector Machine) KNN (K-Nearest Neighbors) iForest (Isolation Forest) AE (Autoencoder)	2021	Sciaenidae (Marine Fish) Barbinae (Freshwater Fish) Mugilidae (Marine Fish)	Accuracy, Precision, Recall F1-Score	Jin et al., 2021	Symmetry
Bangladesh	Fish Species Classification	Not specified	Combination (LBP, SURF, SIFT, CCV, Decision Tree, k-NN, SVM, Naive Bayes, Artificial Neural Networks)	Current Fish Classification Methods	2021	21 Fish Class	Classification Accuracy	Islam et al., 2021	IJITCS
Endonezya	Fish Species Classification	Underwater	Multi-Level Residual VGGNet (MLR-VGGNet)	VGG16, VGG19, ResNet50, Inception V3, Xception	2022	31 Different Types of Fish	Accuracy	Prasetyo et al., 2022	J King Saud Univ Comput Inform Sci
Taiwan	Fish Species Classification	Lake	"C-TTL" (Targeted-fish Transfer Learning)	C-CNN (Complex Background CNN)	2022	10 Different Types of Fish	Not specified	Jiang et al., 2022	Multimedia Tools and Applications
Indonesia	Fish Species Classification	Sea	Backpropagation Sinir Ağı (BPNN)	GLCM, LBP	2022	*Lutjanus ehrenbergii* *Odonus niger* *Myripristis berndti* *Priacanthus tayenus*	5-Layer Cross Validation	Latumakulita et al., 2022	International Journal on Informatics Visualization
Lithuanian	Fish Species Classification	Sea	Deep Learning and TensorFlow Lite Model Maker	EfficientNet-Lite MobileNetV2 ResNet50 EfficientDet-Lite (for object detection)	2022	*Abramis brama* *Cyprinus carpio* *Esox lucius* *Micropterus salmoides* *Perca fluviatilis* *Sander lucioperca*	Not specified	Silva et al., 2022	Sustainability
India	Fish Species Classification	River and Sea	Modified Convolutional Neural Network (MCNN)	Recurrent Neural Networks (RNN), Artificial Neural Networks (ANN) and Support Vector Machines (SVM)	2023	Five Different Types of Fish	Accuracy, Precision, Recall and F-Measure	Prasenan and Suriyakala, 2023	Journal of Combinatorial Optimization

Table 2 shows the diversity and development of international research on fish species recognition and classification. Researchers from various countries (China, Malaysia, Taiwan, Indonesia, etc.) have conducted studies in a variety of environments, including underwater environments, rivers, lakes, and aquariums, to better understand the effects of ecosystems on fish recognition. The use of modern technologies, especially deep learning and machine learning methods, shows the diversity of innovative approaches in this field. Different deep learning models such as CNN, VGGNet, and ResNet as well as traditional methods such as SVM, RF, ANN have been used in the studies. Various metrics such as accuracy, precision and recall were used to evaluate model performance. The results obtained show that deep learning-based methods give successful results in fish species recognition problems. However, factors such as the size of the used data set, model architecture, and data preprocessing methods affect the model performance. For future work, it is recommended to build larger and more diverse datasets, develop new model architectures, and focus on more complex problems such as multi-object detection. These studies have the potential to contribute to important application areas such as fish species tracking, marine ecosystem conservation, and biodiversity monitoring. Future research can add value to this field by developing new data types and analysis techniques to achieve better classification results. Furthermore, the development of automated fish identification systems with further integration of artificial intelligence and machine learning could be an important part of the future of research in this area.

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CHAPTER IV:

APPLICATIONS OF ARTIFICIAL INTELLIGENCE: MARKET PRICE, DISEASE DETECTION, AND FISH FRESHNESS

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This chapter began with the process of identifying the relevant keywords for a systematic review of the current literature. These keywords were chosen in order to capture a large number of articles which could be relevant to the study. The databases that have been searched for this chapter is Science Direct, Google Scholar, IEEE Xplore, Springer Link and Oxford Academic since these databases are reliable and updated databases in the field of aquaculture and fisheries.

Based on the identified keywords, the search strategy was developed in order to identify the articles that could be relevant to the study. While searching for the articles, the titles, abstracts, and keywords of the articles were used. In order to be included in the review, the article had to meet certain criteria, such as being current and relevant, being related in some way to fish market price, diseases and freshnesses, and using machine learning or deep learning in the article.

This was done in order to compare the practices and the efficiency of the methods used in different countries. This

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research is presented in tables, and the information about the scope of each study, the methods used and the results obtained is detailed. This approach offers a sound platform for determining the suitability of the application of deep learning and machine learning approaches in these fields.

4.1. Fish freshness

Fish has been consumed by people for several generations to fulfil their protein requirements and other nutritional needs and is considered healthy by many countries. There are several benefits of consuming fresh fish as it contains proteins and other nutrients that may not be present in other foods to the same extent (Yasin et al., 2023). The conventional methods of determining fish freshness involve physiological, bacteriological and biochemical tests that are costly, cumbersome and destructive (Wu et al., 2024a). The importance of fish quality management has also increased due to the shift towards healthy and nutritious diet and increasing consumption of seafood including fish. The importance of fish quality management has been even more emphasized due to the shift in consumer's trends towards the consumption of healthy foods and the increasing consumption of seafood especially fish (Sipahi et al., 2013; Taheri-Garavand et al., 2020).

Since freshness of fish is a key factor in the fish quality, it is crucial to know the freshness of this highly demanded food product. Thus, the fishing industry has put efforts to develop quick methods to assess the freshness of fish and determine the freshness level. The technology that is currently on the rise and is suitable for the detection of fish freshness is artificial sensors that are replicates of human senses (Madhubhashini et al., 2024). New instruments for the evaluation of fish freshness which are convenient, inexpensive, small, and easy to operate should be designed. They, therefore, require accurate, non-destructive, cheap, precise, and fast techniques to analyse fish freshness (Rehbein and Oehlenschlager, 2009; Dowlati et al., 2013). A lot of research has been done on the identification and freshness classification of fish using chemical, biological or sensor-based methods. Also, research has been conducted on the freshness detection of freshness by applying deep learning algorithms (Yasin et al., 2023).

In recent years, deep learning has been used by researchers and practitioners as a type of machine learning that is known for its ability to process large amounts of data with high level of accuracy. Also, deep learning has helped reduce the difference between the simulated machine intelligence and mechanical data (Le Cun et al., 2015; Salman et al., 2016; Zhao et al., 2019; Akkan et al., 2024). For instance, SVM and ANN such as the support vector machines and artificial neural networks have been applied to the assessment of freshness of fish (Taheri-Garavand et al., 2020; Jayasundara et al., 2023). The results of fish freshness determination studies conducted in different countries are presented in Table 1.

Table 1: The results of fish freshness determination studies conducted in different countries

Country	Application Area	Environment	Proposed Model	Other Compared Models	Year	Type or disease studied	Accuracy Measurement Method	Author	Journal
Spain	Freshness	Local Market	Regression Models and Artificial Neural Networks (ANN)	Unspecified	2013	*Sparus aurata*	R^2, MSE ve MAE	Dowlati et al., 2013	Journal of food engineering
Türkiye	Freshness	Local Market	Artificial Neural Networks (ANN)	Different ANN Architectures and Activation Functions Tested	2015	*Trachurus trachurus*	Unspecified	Atasoy et al., 2015	9th International Conference on Electrical and Electronics Engineering (ELECO)
Philippines	Freshness	Local Market	Image Processing Techniques and Artificial Neural Networks (ANN)	Support Vector Machines (SVM)	2018	*Chanos chanos Decapterus punctatus Oreochromis niloticus*	Unspecified	Navotas et al., 2018	ARPN Journal of engineering and Applied Sciences,
Iran	Freshness	Fish Farm	Deep Learning	Traditional Classification Methods (Artificial Neural Networks, Support Vector Machines, K-Nearest Neighbour)	2020	*Cyprinus carpio*	Accuracy (AC), precision (PR), Specificity (SP), sensitivity (SE), and area under the curve (AUC)	Taheri-Garavand et al., 2020	Journal of Food Engineering
Iran	Freshness	Freshwater source	Artificial Neural Networks (ANN)	Support Vector Machines (SVM)	2020	*Oncorhynchus mykiss*	Accuracy (%)	Lalabadi et al., 2020	Aquacultural Engineering
Greece	Freshness-Maturity	Gulf of Alaska	Bayesian Networks	Support Vector Machines (SVM)	2021	Chinook, Chum, Coho, Pink and Sockeye Salmon.	Confusion Matrix RMSE	Kokkinos et al., 2021	4th International Congress on Applied Ichthyology, Oceanography & Aquatic Environment
Bangladesh	Freshness	Fish Market	CNN-BiLSTM hybrid network	Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Feature extraction algorithms (SIFT and SURF) Inception V3 Model, Artificial Neural Networks	2021	*Oreochromis niloticus*	Confusion matrix, Classification accuracy, Precision, Recall, Specificity, F1 score	Rayan et al., 2021	International Conference on Automation, Control and Mechatronics for Industry
Indonesian	Freshness	fishermen	k-nearest neighbour (k-NN) and Naive Bayes (NB) classification	Unspecified	2022	*Selarides leptolepis*	Unspecified	Yudhana et al., 2022	J. Comput. Sci. Eng
China	Freshness	Fish Market	CNN_LSTM (Convolutional Neural Network_Long Short-Term Memory) model	SVM (Support Vector Machine), BP (Back Propagation) neural network, LSTM (Long Short Term Memory), Logistic equation,	2022	Salmon fish	RMSE ve R^2	Yudhana et al., 2022b	Journal of Food Engineering
Chile	Freshness	Seawater	Neural Network Model	Traditional Statistical Models (Generalised Linear Models - GLM and Generalised Addition Models - GAM)	2022	*Engraulis ringens*	AUC (Receiver Operating Characteristic Curve), Precision Specificity, Recall, False Omission Rate	Armas et al.,2022	Fishes
Türkiye	Freshness	Fish Market	Teachable Machine (TM)	Support Vector Machines (SVM)	2022	*Sparus aurata Dicentrarchus labrax Engraulis encrasicolus Oncorhynchus mykiss*	Accuracy Rate, Confusion Matrix, Monte Carlo Cross Validation	Yavuzer ve Köse, 2022	International Journal of Food Science & Technology

Türkiye	Freshness	Local Market	SqueezeNet and InceptionV3	SVM (Support Vector Machine), ANN (Artificial Neural Network), K-NN (K-Nearest Neighbours), LR (Logistic Regression), RF (Random Forest)	2023	*Oreochromis niloticus*	K-fold cross validation (10-fold) Confusion matrices Performance metrics such as accuracy, precision, recall and F1 score were used.	Yasin et al., 2023	European Food Research and Technology
India	Freshness	Local Market	NasNet-LSTM	Logistic Regression (LR), Support Vector Machines (SVC-R and SVC-L), Decision Tree Classifier (DTC), K-Nearest Neighbour Classifier (KNC), Random Forest Classifier (RFC)	2024	*Oreochromis niloticus, Engraulis encrasicolus, Trachurus trachurus*	Accuracy, Recall, Precision, F1 score, AUC-ROC	Lanjewar et al., 2024	Journal of Food Composition and Analysis
Türkiye	Freshness	Fish Freshness Classification" Data set	MobileNetV2, Xception ve VGG16	Machine Learning Algorithms include Support Vector Machines (SVM), Logistic Regression (LR), Artificial Neural Networks (ANN) and Random Forest (RF).	2024	Fresh and Stale Fish Images	Accuracy, Precision, Recall and F-Score	Kılıçarslan et al., 2024	Turkish Journal of Agriculture-Food Science and Technology
China	Rack Lifetime	Seafood Market in Jinzhou	Radial Basis Function (RBF) model	BP (Back Propagation) model, GA-BP (Genetic Algorithm-BP) model, ELM (Extreme Learning Machine) model	2024	*Sciaenops ocellatus, Epinephelus akaara, Trachinotus ovatus, Larimichthys crocea, Gökkuşağı alabalığı*	MSE, MAE, MAPE, RMSE, R^2	Cui et al., 2024	Food Chemistry
China	Freshness	Sea	ResNet-34 and the attention mechanism (CBAM)	VGG-16 architecture	2024	*Larimichthys crocea*	Model accuracy, precision, sensitivity, specificity, F1 score and AUC (Area Under the Curve)	Wu et al., 2024a	Journal of Food Measurement and Characterization

In recent years, there has been an increased interest in artificial intelligence methods in fish freshness classification studies to prevent freshness loss in the fisheries sector and to protect consumer health. Various machine learning models analyze fish images in different countries to determine freshness. Deep learning has made significant progress, especially in the field of image processing, enabling the better learning of complex features in fish images and achieving higher accuracy rates. Table 1 provides a comprehensive overview of the practices for fish freshness and maturity assessments in different countries. Studies in countries such as Nigeria, Iran, Indonesia, Greece, Spain, India, Türkiye, Bangladesh, China, the Philippines, and Chile have often focused on practical areas such as fish markets, fish farms, and local markets. Machine learning and deep learning techniques stand out among the models used in the studies; for instance, Nigeria prefers classical methods like K-NN, SVM, LR, RF, and ANN, while India and Bangladesh use more complex models like NasNet-LSTM and CNN-BiLSTM hybrid networks. Research has also focused on specific fish species, with the use of hybrid models (e.g., CNN-LSTM) and transfer learning methods (e.g., MobileNetV2, VGG16). The most frequently studied species include nile tilapia, carp, salmon, and mackerel.

Studies have used various metrics as accuracy measurement methods; among these metrics, criteria such as accuracy, F1 score, recall, precision, and AUC-ROC curve stand out. In Recent years, particularly in the period 2022-2024, have witnessed the use of increasingly complex and effective models. Overall, this table reveals the diversity and international dimension of research on fish freshness and maturity and shows that machine learning and deep learning applications are increasingly present in the fish industry. These findings provide an important basis for improving the effectiveness of the methods used for fish freshness assessments and improving practices in the industry. Some countries have compared traditional statistical methods, such as regression models, with modern machine learning techniques to evaluate the differences between these approaches. In addition, many studies have collected data from fish markets and local sources, emphasizing the importance of practical applications that are compatible with local economies. All these data comprehensively present the existing research on fish freshness and reveal innovations and developments in this field through various methods.

4.2. Fish disease detection

Fish diseases hinder small- and large-scale fish farming. Manual observation methods are insufficient for accurate detection. Advances in technologies offer highly accurate early disease detection, preventing losses and ensuring the safety of vulnerable fish, making early detection crucial for their survival (Rakesh et al., 2023).

Fish diseases seriously threaten nutritional safety in aquaculture. Due to the lack of adequate infrastructure, it is still difficult to detect diseased fish at an early stage in aquaculture. It is very important to identify sick fish as soon as possible to prevent the spread of the disease (Ahmed et al., 2022). Fish diseases are a major challenge to the fishing industry because they affect a large number of fish and spread fast. It is quite common to observe that the experienced farmers mostly use traditional manual diagnostic methods which are rather time-consuming and can be inaccurate at times. There is a need for a fast and cheap solution to this problem to protect the fishermen as well. Fish diseases are a big concern in the management of fisheries. It can also help in checking the spread of disease and mortality since the detection is done early. However, traditional approaches may not be very effective. The following are some of the ways through which AI can help in the detection of diseases given fish images and videos (Vasumathi et al., 2024). The advancement in the machine learning (ML) and computer vision technologies provide effective techniques for identifying the diseases in the fish and monitoring their growth. Machine learning algorithms can identify and predict anomalies, diseases, and stress indicators. Fish diseases show both physical and behavioral symptoms (Lou et al., 2007; Huang et al., 2023). Machine learning algorithms can detect early indicators of diseases, parasites, or abnormalities in the appearance and behavior of fish through image analysis and pattern recognition. These features allow fish diseases to be diagnosed and categorized using machine learning based on image processing (Ahad et al., 2024). Machine learning techniques and artificial intelligence algorithms have been successfully used to develop models using historical data from fish farming applications, yield, and environmental measurements to aid decision-making and to detect/predict disease outbreaks (Rahman & Tasnim, 2014; Islam et al., 2024). The results of fish disease detection studies conducted in different countries are presented in Table 2.

Table 2: The results of fish disease detection studies conducted in different countries

Country	Application Area	Environment	Proposed Model	Other Compared Models	Year	Type or disease studied	Accuracy Measurement Method	Author	Journal
Bangladesh	Fish Diseases	Unspecified	Deep learning models (especially VGG16 and VGG19 ensemble model)	ResNet-50, Random Forest and Miscellaneous Machine Learning	2021	Four different diseases: White Spot, Black Spot, Red Spot and Fresh Fish	Performance evaluation matrices	Reddy et al., 2021	International Journal of Engineering Science and Advanced Technology (IJESAT)
Bangladesh	Fish Diseases	Lake	K-means and C-means fuzzy logic clustering and classification with Multiple Support Vector Machines (M-SVM)	Unspecified	2021	20 species	Accuracy Rate	Sikder et al., 2021	Int. J. Adv. Comput. Sci. Appl. (IJACSA)
Saudi Arabia	Fish Diseases	Fish Images from the Internet and Some Aquaculture Companies	Support Vector Machines (SVM) model.	Decision tree, logistic regression and naive Bayes.	2022	Salmon fish	Accuracy, precision, sensitivity, recall, specificity, F1 score and ROC curve	Ahmed et al., 2022	Journal of King Saud University-Computer and Information Sciences
Malaysia	Fish Diseases	Unspecified	Convolutional Neural Network (CNN)	Deep Learning and Machine Learning	2022	White spot and red spot disease	Accuracy Rate	Hasan et al., 2022	International Journal of Nonlinear Analysis and Applications
Unspecified	Fish Diseases	Data, Kaggle, Social Media Sites, Websites	ResNet-50.	VGG16, VGG19, Ensemble Models (VGG16+VGG19, VGG16+InceptionV3), Random Forest, XGBoost.	2023	Fish diseases (red spots, black spots, white spots, fresh fish).	Accuracy, F1-score	Mamun et al, 2023	International Journal of Computer Applications
India	Fish Diseases	Local Water Resources and Aquaculture Facilities	Machine Learning Techniques	Traditional Physical Observation Methods	2023	Various Freshwater and Saltwater Fish Species	Standard Statistical Metrics	Rakesh et al, 2023	International Conference for Emerging Technology
China	Fish Diseases	Sea	MobileNet v3-GELU-YOLOv4	YOLOv4, MobileNet v1-YOLOv4, MobileNet v2-YOLOv4, MobileNet v3-YOLOv4.	2023	Fish with diseases of hemorrhagic septicemia, saprolegniasis, benedeniasis and scuticosiliatosis.	Precision (accuracy), Recall (recall), mAP (average accuracy) and FPS (frames per second).	Yu et al, 2023	Fishes
China	Fish Diseases	Ornamental Fish Market	YOLOv4 (You Only Look Once version 4)	YOLOv3, YOLOv4-Lite, YOLOv4-tiny and CenterNet.	2023	*Ichthyophthirius multifiliis* *Gyrodactylus kobayashii* *Argulus japonicus*	mAP (mean Average Precision) Precision Recall Precision-Recall Precision-Recall curves (PR curves) F1 score	Li et al, 2023	Aquaculture
India	Fish Diseases	Sea	Convolutional Neural Networks (CNNs)	Machine Learning and Deep Learning Algorithms	2024	Unspecified	Unspecified	Vasumathi et al., 2024	International Conference on Science Technology Engineering and Management

Between 2021 and 2024, researchers from various countries, including India, Bangladesh, Saudi Arabia, and Malaysia, conducted the studies listed in Table 2. All these studies focused specifically on the detection of fish diseases. Among the models used, deep learning techniques such as convolutional neural networks (CNNs), ResNet-50, VGG16, and VGG19 stand out. Comparisons with other machine learning algorithms show that CNNs generally achieve higher accuracy rates. However, other methods such as Support Vector Machines (SVM), Random Forest, and XGBoost also give successful results in some cases. This shows that the characteristics of the data sets are important in determining the most appropriate method for different fish species and diseases. The studies utilized information from a variety of settings, such as social media, Kaggle, lakes, and seas, as data sources. These different data sources illustrate the diversity and challenges of data collection methods. The diseases under consideration include particular variants of fish illness including red spot, white spot and other diseases of freshwater and saltwater fish. The accuracy measurement methods of the studies are usually based on performance evaluation matrices, such as accuracy, F1 score and precision. This is a common approach to assessing the effectiveness of models. The research was conducted on particular types of fish diseases including red spots and white spots and the detection of these diseases involved the use of modern data sources. The table shows that the research on fish diseases has been on the rise with more and more incorporation of machine learning and deep learning in it. This presents an important application area in the fish farming and aquaculture industries. All the studies in the table prove that artificial intelligence-based methods are an essential tool for the diagnosis of fish diseases and CNNs are particularly effective in analyzing fish images for disease symptoms. Nevertheless, more research is needed in order to determine which method is the most appropriate for different types of fish and diseases. Finally, the following studies were conducted by researchers during the period 2021-2024 which shows the increasing trend of fish disease research and the crucial role of technology. The involvement of various research groups shows that the topic has been explored from different angles. Overall, Table 2 stresses on the need of utilizing advanced management and technology for the health of fish and their diseases.

4.3. Fish price forecast

Seafood price changes influence the decision-making of producers, consumers, governments and other stakeholders. It is important for decision-makers and other stakeholders to understand changes in seafood prices (Mutlu et al., 2018). This chapter aims at developing a reliable and accurate marine fish price forecasting model to avoid the adverse consequences of unforeseen events on human beings (Wu et al., 2024b). The prices in the seafood market are key factors that define the complex fishing industry activities including grading, transportation, storage and processing (Holma et al., 2019). It was also noticed that the price fluctuations in fish affect food and nutrition security in a certain way, particularly for the food insecure and the landless (Bennett et al., 2021). Hence, the accessibility of information on market prices, fish prices by region fish and price the forecast accurate is crucial to ensuring the sustainability of the fisheries management systems and maximum utilisation of resources (Pan, 2021). The research methods in the field of marine fish price forecast differ a lot, but one of the major concerns is to forecast the price of marine fish. Marine fish price is a classic example of a complicated time series that poses a severe challenge to effective forecasting due to the characteristics of volatility and non-linearity. Two of the most commonly applied traditional econometric techniques for price forecasting include the exponential smoothing (ETS) model as shown by Cao (2019) and autoregressive integrated moving average (ARIMA) model as described by Wu et al. (2016).

Table 3: The summary of studies on price forecasting of fish species with neural networks in different countries

Country	Application Area	Environment	Proposed Model	Other Compared Models	Year	Type studied	Accuracy Measurement Method	Author	Journal
Norway	Fish Price Forecast	Farmed Atlantic salmon	Long Short-Term Memory (LSTM)	ARIMA, GARCH, SARIMA	2018	Atlantic Waders	RMSE, MAE, MAPE, MASE	Bloznelis, 2018	Journal of Forecasting
Norway	Fish Price Forecast	Fish Pool ASA	Markov-switching model (MSM) and multifactor model (MFM)	Multifactor model (MFM)	2021	Salmon	Parameter estimation accuracy Information criteria (AIC, HQC, BIC) RMSE	Xiang et al., 2021	Journal of Modeling in Management
Vietnam	Shrimp Price Prediction	Shrimp exported from Vietnam	Random forest and gradient boosting algorithms	ARIMA (Auto Regressive Integrated Moving Average) Linear regression Artificial neural networks K-nearest neighbor (KNN)	2021	Vietnamese Shrimp	MAE MSE MAPE MSPE	Khiem et al, 2021	Fisheries Science
Vietnam	Shrimp Price Prediction	Unspecified	Random Forest * Gradient Boosting	Support Vector Regression, Neural Networks, Time Series Models	2022	Vietnamese Shrimp	MAE, MSE, RMSE	Khiem et al., 2022	Plos One
Mexico	Lobster Price Prediction	Baja California peninsulas	NARX model	ARIMAX (Autocorrelation Integrated Moving Average) model.	2022	*Panulirus interruptus*	MSE, MAE, R^2	Hernández-Casas et al., 2022	Applied Sciences
China	Fish Price Forecast	Marketing and Information Department of the Ministry of Agriculture and Rural Affairs of China	Variational Modal Decomposition - Improved Bald Eagle Search - Long Short-Term Memory Network (VMD-IBES-LSTM)	EMD-VMD-LSTM VMD-LSTM CEEMD-CNN-LSTM MOGWO-LSSVM	2022	Grass Carp (Carp family) Crucian Carp (Golden Fish) Carp (Deaf Fish) White Chub (White Stick) Big Scallop (Big Scallop)	MSE, RMSE, MAE, MAPE	Wu et al., 2022a	Agriculture
Norway	Fish Price Forecast	Norsk Råfisklag, Norges Bank, Fishpool and SSB datasets	SARIMAX	ARIMA, SARIMA, LSTM	2023	Salmon	RMSE	Bjørnstad et al., 2023	Bachelor's thesis, NTNU
China	Fish Price Forecast	Sea	PSO-CS Weight Allocation Method (Particle Swarm Optimization and Cuckoo Search algorithm)	LSTM (Long Short-Term Memory) ELM (Extreme Learning Machine) ETS (Exponential Smoothing Forecasting Method)	2024	*Great amberjack*	MSE, RMSE, MAE, MAPE, SMAPE	Wu et al., 2024b	Foods
Taiwan	Fish Price Forecast	Fish Market	Hybrid Model	Linear regression Support Vector Machines (SVM) (RBF, linear and polynomial kernels) Random Forest Long Short Term Memory (LSTM) network	2024	*Oreochromis mossambicus* *Oreochromis* spp. *Chanos chanos* *Lates calcarifer* *Micropterus salmoides* *Lateolabrax japonicas* *Epinephelus lanceolatus* *Eleutheronema rhadinum*	R^2, MAE, MAPE, MSE, MSPE	Lai et al., 2024	Aquaculture
Brazil	Fish Price Forecast	Pernambuco Supply and Logistics Center	Long Short Term Memory (LSTM) Neural Network	FbProphet Library	2024	*Sardinella brasiliensis*	Unspecified	França et al., 2024	Marine Resource Economics

The studies presented in Table 3 consolidate the methods and models used in various countries, as well as the fish price forecasting studies conducted in different countries, showcasing a variety of approaches in this field. These studies apply statistical and machine learning models to analyse the fluctuations in price of the fisheries sector and to make predictions about the future trends of prices. Taiwan preferred hybrid models and worked with a large number of fish species including tilapia and red tilapia while China used a complex model called PSO-CS weight allocation method.

There are certain artificial intelligence techniques that are used quite often in research such as Long Short-Term Memory (LSTM) and Random Forest; LSTM is known to have ability to process time series data. Also, it is necessary to compare the proposed models with traditional approaches. For instance, the Taiwanese study assesses the feasibility of techniques including linear regression and support vector machines. This is because it is crucial to know the strengths and weaknesses of the various algorithms that are in use.

In the period between 2021 and 2024, researchers carried out their research on different types of fish and seafood species with more emphasis on the Vietnamese shrimp and Atlantic salmon. Measures of forecast accuracy include Mean Square Error (MSE) and Root Mean Square Error (RMSE). Some of the studies have also assessed the performance of the model using statistical measures such as the coefficient of determination (R^2). In general, these data evidence that the research on seafood price forecasting is relevant and is being developed at an international level, despite the existence of different approaches in the several countries. Furthermore, the findings of these researches assist in enhancing the effectiveness of the strategies that are used in the seafood market. To summarize, fish price forecasting is a significant issue in the fisheries industry. These studies offer valuable insights to the fishers, consumers, and policy makers. However, more research is needed to gain better and more accurate outcomes.

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CHAPTER V:

APPLICATIONS OF TRADITIONAL EVULATION: RELATIONSHIPS BETWEEN MOUTH DIMENSIONS AND FISH LENGTH IN PIKE (*ESOX LUCIUS* L., 1758) INHABITING SIDDIKLI DAM LAKE

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INTRODUCTION

In fish species, mouth dimensions (vertical and horizontal mouth gape and mouth area) and their relationships with body length are critical parameters in the study of fish feeding biology. These metrics are essential for determining the maximum prey size and resource utilization by predatory species (Mihalitsis and Bellwood, 2017), defining the ecological position of predators within the food web (Karpouzi and Stergiou, 2003), identifying size-dependent feeding characteristics (Yazicioglu et al., 2018), understanding predator-prey relationships (Magnhagen and Heibo, 2001; Yazicioglu, 2018), and determining the prey types consumed (Paul et al., 2017). Vertical mouth gape plays a significant role in prey capture by predators and simultaneously limits or controls the size of the captured prey (Cunla and Planas, 1999). Mouth dimensions represent the maximum size of prey that a fish can swallow, and ontogenetically, larger fish

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are capable of consuming larger prey items, as indicated by their mouth dimensions (Ridwan et al., 2020).

Pike (*Esox lucius*) is a highly specialized piscivorous species for most of its life, despite consuming a wide range of prey items, from invertebrates to fish. Its ability to capture and consume prey is determined by both its own size and the size of its prey, specifically the predator-prey size ratio (Craig, 2008). The size, shape, and positioning of the mouth, combined with tooth type, provide critical insights into the feeding habits of a fish. For piscivorous fish that swallow their prey whole, feeding performance is closely linked to mouth gape, pharyngeal gape, and cleithrum width (Mihalitsis and Bellwood, 2017). Measurements such as vertical and horizontal mouth gape are particularly important in determining how effectively a fish can capture its prey. Therefore, investigating the relationships between mouth dimensions and fish length plays a critical role in understanding feeding preferences, predator-prey relationships, and feeding behaviors. These measurements also enable one to determine the fish's capacity to accommodate the various conditions within its environment and also aid in explaining the predator-prey relationship within ecosystems.

This study aims to define the morphometric relationships between mouth dimensions and fish length in *Esox lucius* inhabiting the Sıddıklı Küçükboğaz Dam Lake.

MATERIALS AND METHODS

This research work was conducted on *Esox lucius* which are found in Sıddıklı Dam Lake. The construction of Sıddıklı Dam Lake started in 1998 and was completed in 2009. The dam lake was constructed for irrigation and has a volume of 28. 5 hm^3 with a surface area of 1.65 km^2 and a dam height of 53 meters (Yazıcı, 2018). Sıddıklı Dam Lake is important to Kırşehir as it supplies water for the irrigation of large farms (Akkan et al., 2018).

Sample collection was done every month for a period of September 2015 to August 2016. One hundred thirty-three pike were captured. The total length (TL) of the fish was measured with an accuracy of ±0. 1cm by using a ruler. The following measurements were taken in the pike specimens: Vertical mouth gape (MV) and horizontal mouth gape (MH) were measured with an electronic caliper with an accuracy of 0. 01mm.

The size of vertical mouth gape was assessed as the gap between the upper and lower jaws when the mouth of the fish was completely open (Czerwinski et al., 2008; Mihalitsis and Bellwood, 2017). Horizontal mouth gape was measured as the length of the upper and lower jawbone joints articulation on the left and right sides of the fish when the mouth was fully extended (Czerwinski et al. 2008; Mihalitsis and Bellwood 2017).

This study investigated the relationships between mouth morphometry and fish length. To determine these relationships, vertical mouth gape (MV), horizontal mouth gape (MH), mouth area (MA), and total length (TL) values of the samples were utilized. In pike, the mouth area (MA) was determined using the elliptical model calculated from vertical and horizontal mouth gape measurements, applying the following formula (Erzini et al., 1997; Czerwinski et al., 2008).

$MA = 0.25 x \pi (MV \ x \ MH)$

Where:

- **MA** = Mouth area (elliptical) in cm²
- $\mathbf{M_V}$ = Vertical mouth gape in cm
- $\mathbf{M_H}$ = Horizontal mouth gape in cm
- $\boldsymbol{\pi}$ = Pi constant (approximated as 3 for simplicity)

This formula assumes an elliptical shape to estimate the mouth area based on the vertical and horizontal gape. The relationships between mouth dimensions and fish length in pike were determined using a linear regression model (Karpouzi and Stergiou, 2003; Czerwinski et al., 2008; Contente et al., 2009).

RESULTS

A total of 133 specimens of *Esox lucius* L., 1758 were examined for this study. The minimum, maximum, and mean values of mouth morphometric measurements (MV, MH), mouth area (MA), and total length (TL) are presented in Table 1.

The total length of the samples ranged from 23.40 cm to 86.60 cm, with a mean total length of 53.83 cm (SE = 0.912). Vertical and horizontal mouth gapes (MV and MH) were found to range between 3.40–13.00 cm and 2.10–11.00 cm, respectively. It was observed that the vertical mouth gape was larger than the horizontal mouth gape. The mouth area (MA) of the 133 specimens examined ranged from 5.77 cm^2 to 112.26 cm^2.

Table 1: Descriptive statistics for total length and mouth morphometric characteristics in pike (*N*: sample size, *Min*: minimum, *Max*: maximum, *Mean*: mean, *Se*: standard error)

Measurements (cm)	N	Min	Max	Mean	Se
Total length (TL)	133	23.40	86.60	53.83	0.912
Vertical mouth gape (M_V)		3.40	13.00	7.31	0.128
Horizontal mouth gape (M_H)		2.10	11.00	5.65	0.120
Mouth area (elliptical) (cm^2)		5.77	112.26	33.78	1.320

Significant relationships were found between vertical mouth gape (M_V), horizontal mouth gape (M_H), mouth area (MA), and total fish length (TL) ($P < 0.001$), with r^2 values exceeding 0.671 (Figures 1–4). Examination of the regression equations revealed that mouth dimensions increase progressively with fish length (Figures 1–2). Among the regression analyses, the strongest linear regression relationship was observed between total length and horizontal mouth gape ($P < 0.001$, $r^2>0.759$) (Figure 2).

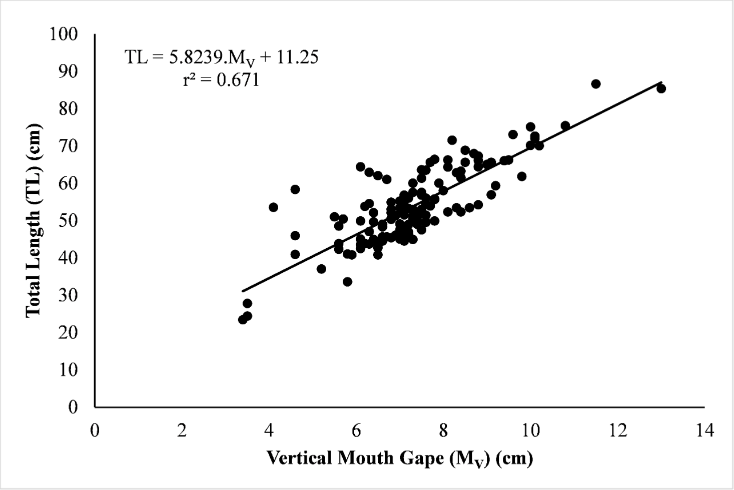

Figure 1: Relationship between vertical mouth gape and total length

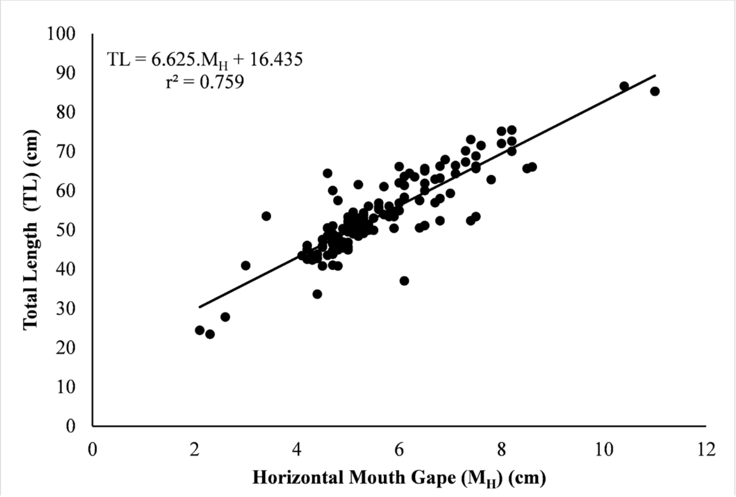

Figure 2: Relationship between horizontal mouth gape and total length

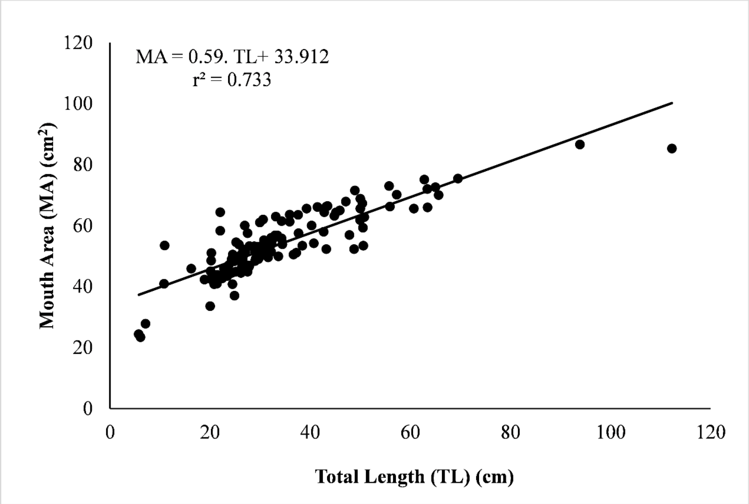

Figure 3: Relationship between mouth area and total length

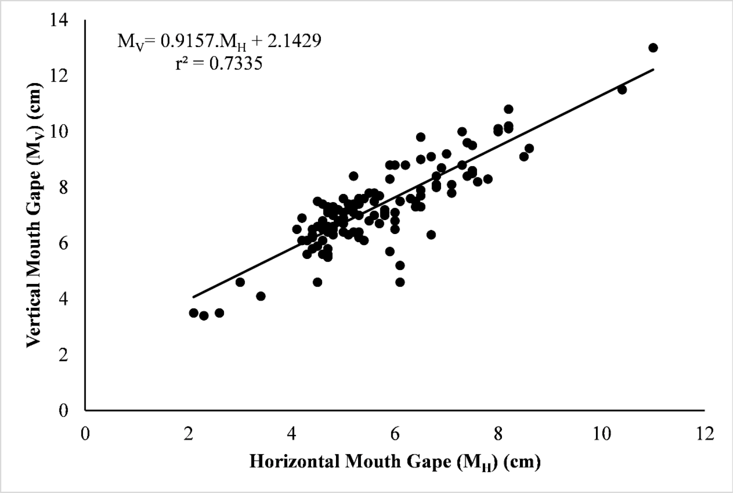

Figure 4: Relationship between vertical mouth gape and horizontal mouth gape

DISCUSSION

In *Esox lucius* inhabiting Sıddıklı Dam Lake, strong linear relationships were identified between mouth dimensions and fish length (TL-M_V, TL-M_H), mouth area and fish length (MA-TL), and vertical and horizontal mouth dimensions (M_V-M_H) (Figures 1–4). Similarly, a study on the same species from Lake Ladik reported strong linear relationships between predator size and mouth dimensions (Yazicioglu et al., 2018).

Kyritsi and Moutopoulos (2018) described the relationship between mouth morphometric characteristics and fish length in pike using a power model, with r^2 values exceeding 0.812. In the Eastern Mediterranean, relationships between vertical mouth gape and predator total length in 18 different marine fish species were explained using a linear regression model for 10 species, while a logarithmic linear model was used for the remaining 8 species (Karpouzi and Stergiou, 2003).

Pike (*Esox lucius*) populations from different habitats are known to exhibit strong relationships between mouth dimensions and total length (Nilsson and Brönmark, 2000). In this study, it was observed that as fish length increased, mouth area (MA), vertical mouth gape (MV), and horizontal mouth gape (M_H) also showed a tendency to increase. Similarly, Magnhagen and Heibo (2001) reported that mouth gape increases parallel to total fish length. In addition, this study found the closest link between mouth dimensions and fish length was between horizontal mouth gape and fish length. Mihalitsis and Bellwood (2017) noted that in the majority of fish, the prey fish are swallowed while being laid horizontally in the mouth. Therefore, it is likely that horizontal mouth gape is a more constraining factor than the vertical gape.

Karpouzi and Stergiou (2003) found out that mouth size and shape are variables that are influenced by fish length and trophic level with the predator fish at the higher trophic level having larger mouth size that would enable them to capture larger prey. Here, the mouth gape was observed to be greater in the vertical direction than in the horizontal direction. The same conclusion was made by Koundal et al. (2016) who stated that vertical mouth gape grows faster than the horizontal mouth gape possibly because of the variation in diet and feeding habits.

CONCLUSION

In conclusion, if mouth dimensions in fish can be predicted from other easily measurable morphometric traits like length or weight that can be taken in the field, then it becomes possible to assess the predatory effect of a natural fish population. Also, with increasing body length there is an increase in the width of the mouth gape seen which shows the adaptation towards the feeding behavior. The results of this study are important for the analysis of competition in the food webs consisting of the predator species such as pike, which are the object of concern in the majority of the fisheries management plans.

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CHAPTER VI:

GENERAL EVALUATION AND CONCLUSION

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Given that fisheries have the potential for exploitation, especially when other resources are in unfavorable conditions, management plans need to be developed with a holistic approach to support the effective use of resources and the communities that use them. Within this framework, models that forecast population and resource capture behaviors significantly contribute to various actors' decision-making processes and swiftly adjust to evolving scenarios. These forecasting models serve as critical tools to assess the impacts of different scenarios and optimize resource management strategies (Cavieses Núñez et al., 2018). As noted by Chavez et al. (2008) and Gutiérrez et al. (2016), one step toward bridging knowledge gaps in this fishery and assisting strategies for sustainable and ecosystem-based management is the application of new tools and approaches that can account for various forms of ecosystem variability (including the stresses caused by climate change).

It is imperative that the fisheries management authority comprehensively evaluate the results of these studies in order to develop and implement a sound management plan that will ensure the sustainability of stocks and promote rational management (Şahin and Ceylan, 2023). Fluctuations in climatic and oceanographic variables in the marine environment affect

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productivity and species distribution in the ecosystem, with particularly important effects on the abundance of anchovies and sardines and their interactions within the ecosystem. Large-scale environmental changes affect the population dynamics and survival rates of these species, particularly through factors related to food availability (Plaza-Vega et al., 2024).

Although deep learning methods show considerable potential in aquaculture, they face challenges such as large sample sizes and complex data requirements. For example, fish disease and behavior data is difficult to collect, and there are not enough public (private) databases. In addition, other important factors that require continuous research and development activities include the deep learning applications as there would be need for specialized equipment to collect and process data in this area of study (Sun et al., 2020).

Fish age estimation accuracy is essential for fishery management and conservation activities (Megrey, 1989; Campana, 2001). Deep learning techniques are not widely utilized and the age estimation algorithms now in use are based on small data sets. To increase forecast accuracy, biological and spatial data must be integrated. Furthermore, the credibility of results is reduced by other research' lack of multimodal techniques and long-term datasets (Benson et al., 2023).

Age data is used to assess fish population health, monitor population trends, and develop suitable management strategies in order to ensure the long-term sustainability of fish stocks (Campana, 2001; Bianchini and Ragonese, 2011; Carbonara and Follesa, 2019). Complete automation, smart sensors, disease detection, energy efficiency, data analysis, environmental impact assessment, cost-effectiveness, standardization, and species-specific systems are among the other areas of smart aquaculture that require more research and development (Vo et al., 2021). Actual event applications, variety of species, scaling real-time processing, and cost-effectiveness are all areas where fish size measurement methods require improvement.

There is need to conduct more research on multi-species analysis, long-term impact assessment as well as the integration of artificial intelligence in the system (Ankitha et al., 2024). This is because, while machine learning can be used to identify fish diseases, it is crucial that those managing the fish farmers have adequate knowledge on the technologies. The effort and experience of the farmers and clinicians are important in the determination of disease status and this enhances the overall diagnostic framework and accuracy (Islam et al., 2024). As the use of artificial intelligence in marine fisheries and aquaculture expands, it also presents a range of challenges. In particular, due to the low visibility and complexity of underwater environments, processing fish images based on light vision poses problems such as fish overlap, low resolution and fuzzy outlines.

While intelligent analysis of water quality provides real-time performance and high efficiency, it needs to overcome problems such as the high cost and simple wear of sensors in seawater. Furthermore, smart feeding decisions save feed and improve labor productivity, but accurate automatic feeding requires precise models that monitor fish growth, estimate biomass, and analyze feeding behavior (Zhang and Gui, 2023). Data analysis reveals that deep learning-based techniques outperform machine learning-based techniques despite having a sophisticated design that is very difficult to understand. Moreover, deep learning-based methods can work effectively with less labeled data. Data processing, data annotation, data quality, and imbalanced datasets are some of the obstacles and constraints that machine learning and deep learning applications still have to deal with despite their success (Yassir et al., 2023). Existing studies have not provided more detailed information on the limitations of the datasets, the shortcomings of image preprocessing methods, and the performance evaluation criteria of the algorithms. A more comprehensive discussion of future trends and challenges is covered. Other studies have generally not adequately addressed these issues. There is a need for studies that address the issues and needs specific to aquaculture in more depth.

Studies have generally focused on a narrower, limited number of fish species. The use of datasets covering a wide range of species is lacking. Studies in the literature often estimated only a single biometric trait (length or weight). The literature has not adequately addressed the estimation of multiple biometric traits such as length, circumference, and weight. Data access and quality issues exist, including imbalanced data distribution and the processing of images from various media. Challenges remain in the correct application of deep learning models, the use of model ensembles, and the implementation of algorithms such as transfer learning. Collaboration between marine ecologists and computer scientists needs to be improved, and machine learning methods need to be better integrated. There are applicability issues, such as testing the developed models in real-world conditions and developing user-friendly software tools. Appropriate methods need to be developed for fish monitoring in real-world uncontrolled underwater conditions, but so far there has been limited success. It is thought that data diversity should be increased and more advanced machine learning algorithms should be used. Addressing these shortcomings will contribute to obtaining more reliable and applicable results in the field of fish mass estimation. The literature noted a lack of data diversity, difficulties in implementing deep learning models, issues with unbalanced data sets, and insufficient research on automation of acoustic fish species identification processes. Future studies can utilize larger data sets, evaluate model performance more comprehensively, and interpret results more effectively.

Consequently, the integration of artificial intelligence methodologies improves the creation of novel strategies to guarantee the sustainability of fish, an essential group with a biological presence. In coming decades, wider adoption of these technologies will aid in the maintenance of marine habitats and the sustainable management of fish populations. It is crucial for policymakers to establish measures that facilitate technological transition and promote its adoption. In this scenario, alongside the advantages offered by artificial neural networks, it is essential to improve collaboration and information exchange for sustainable fishing.

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