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Utilizing Deep Learning for Morphological Analysis of Fish Species in Large Databases

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Abstract
With the use of Deep Learning algorithms, it is conceivable to identify the object characteristics in an image or video frame as a collection of landmarks. To regulate the size of the fish and the location of its mouth and fins, eight landmarks are aligned after object identification and image segmentation are completed to isolate a fish in an image. This study included four common Mediterranean fish species: Diplodus palazzo, Sparus aurata (sea bream), Dicentrarchus labrax, and Merluccius merluccius (cod fish). Fish farms are used to raise the first three of these species. Ichthyologists are thus particularly interested in tracking these fishes' morphological characteristics in their natural habitat, and the suggested approach can help with this. Convolution neural networks and OpenCV were used in Python and MATLAB applications to build the suggested approach. Furthermore, we offer a thorough analysis of the leading deep learning methods for monitoring fish habitat, such as segmentation, classification, enumeration, and localization. Additionally, we evaluate several DL approaches in the underwater fish monitoring domains and investigate publically accessible datasets. We also review some of the difficulties and possibilities in the new area of deep learning for analyzing fish habitats. This publication is intended to guide marine researchers who wish to gain high-level knowledge of DL, follow our detailed tutorial to build it for their applications, and observe how it is developing to support their research. Additionally, it is appropriate for computer scientists who wish to examine cutting-edge DL-based techniques for monitoring fish habitat.

Keywords: Deep Learning (DL), Morphological Analysis (MA), Fish Species (FS), Large Databases (LD)

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Introduction
Models connected with deep learning process information like the human brain. These models apply to many procedures that people mostly do. Deep learning applications can be seen in various places, such as the recognition of images in various tools, the recognition of NLP, and speech software. One type of machine learning is deep learning, in which artificial neural networks are utilized to learn from data. Artificial neural networks are synthesized by following the algorithm of the human brain. These networks prove helpful for finding solutions for a large number of issues. Some areas included in it are image recognition, the processing of natural language, and speech recognition(Goodwin et al., 2022). The procedures of deep learning are based on the large sets of data that are labelled. This procedure usually creates a connection between data and their accurate labels. For instance, let's consider the example of a task involving recognition of an image. The procedure may involve the learning association between certain characteristics of an image along with the correct labelling. Once the learning procedure is understood, it can be used to build predictions about the newly attained data(Zhao et al., 2021). These things can be understood with the help of an example like the procedure of deep learning that is designed for building an understanding of images of dogs, making it possible for dogs found in other things to be recognized. Deep learning can only be possible with the help of artificial neural networks because they prove helpful in learning from new data. The building blocks of neural networks are interconnected nodes. The action learns a specific character of the data of each node. Let us recall the previous example based on an image; in an image recognition network, the first layer of nodes plays an important role in

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identifying edges. The second proves helpful in the identification of shapes and objects identified by the third layer(Simović et al., 2024). Artificial intelligence is the base of both deep learning and machine learning. However, machine learning is very wide and covers many deep learning topics. Deep learning and machine learning procedures can only be practised for labelled or unlabeled data. However, the type of work and its procedure play an important role in this process. Machine and deep learning are useful in image recognition, speech recognition, and natural language methodology. Most of the time, deep learning gives outstanding classic machine learning. It is mostly seen in the tasks in which recognition of complex patterns is involved. The following things are included in this phenomenon: image classification and recognition of images because it can learn graded data representation(Schwartz, 2021). There are various types of deep learning, including convolutional neural networks, deep reinforcement learning, and recurrent neural networks. The way of identifying, structuring, and investigating the complete set of all relationships that a multidimensional issue complex can accompany is known as morphological analysis. Morphological analysis is based on two words. One is identifying morphemes and then analyzing the arrangement of morphemes in words(Rathi, Jain, & Indu, 2017). The challenges of productive and non-productive types come from morphological analysis. Ambiguous morphological analysis also comes in this way. The term finite state automata is usually utilized for morphological parsing and recognition. The study of the formation of words and the rules that need to be followed while word formation comes under the morphology category(Fontes et al., 2024). The latest research on fish species databases shows that more than 35000 fish species are found. The connection of these species is with 623 families around the world.

Fish Base is a term for a global species database about various fish species. It is the largest database that can be accessed easily and is about adult fish on the web. It is transformed into a dynamic, versatile, and ecological tool with time. It is commonly cited in scholarly publications. In life science research, zebrafish is the most studied species. The whale shark, also known as Rhincodon, is the largest fish. Whale sharks, whose length can be 4m to 12m, can be seen easily, but the length of 18m in fish is very hard to see(Yang et al., 2021). The colour pattern of whale sharks plays an important role in recognition of sharks. These water bodies can be large or small in size. Many methods for the classification of fish are usually based on this procedure. Outside of water, the underwater classification process has to face various issues like noise in the background, breaking of images, the appearance of other water bodies found in the image, and the quality of the image that is found under the water level. The technique utilized in this method has a strong connection with convolutional neural networks(Wäldchen & Mäder, 2018). It also connects with deep learning and image processing to achieve an accuracy of 96.29%. A surety is found about the accuracy of discrimination betterments than previously proposed methods. This study shows that a deep learning neural network is built to seem like a real-time, advanced, and constructive method, which appears to be very useful in obtaining knowledge about fish species(Garcia et al., 2020). It is very useful to automate and identify the carp species, which are very important economically. Identifying fish species proves very helpful for biologists in understanding fish species. To have an eye on the behaviour of different species of fish, observation of their behaviour is very important so that the inner system of marine life can be analyzed. Fishery industries and aquaculture need to have information about the identification of species of fish. This observation is also essential for stock management concerning water bodies and aquatics monitoring(Banan, Nasiri, & Taheri-Garavand, 2020).

Research Objective

The main objective of this research is to suggest all the methods by which the classification of fish species is automatically involved. The classification of fishes should be done accurately so that the behaviour of fish can be understood easily in the field of Ichthyology and by biologists related to marine. Concerned institutions aim to estimate the presence of several fishes of one type and the presence of endangered in water bodies.

Literature Review

Researchers claim that the fish identification process uses advanced technology systems. deep learning algorithm, when used along with IoT, provides the basis for separating fish species based on their morphological characteristics. Deep learning algorithms provide a large database related to fish taxonomy(Ahmed, Hossain, Rahman, Uddin, & Islam, 2023).studies reveal that fish is an important source of nutrients for the human body. Humans consume fish oils to obtain essential vitamins and minerals. Using a healthy fish to extract oil holds great significance. To classify healthy fish, the information is obtained from imagery-based data deep learning algorithms extract useful data from fish images and then determine the quality of fish(Aziz, Desai, & Baluch, 2023).studies suggest that remains of fish species tell about the ecological changes that occurred in the past .different methods are used to identify various remains of fish species .machine learning approach is used to find out the remains of bimolecular fish species for developing taxonomical data the use of ID3 algorithm is made in fish taxonomic classification process(Baker, Harvey, & Buckley, 2023).Studies suggest that using the VR approach helps determine the morphological data related to fish species. the classification of fish species is based on its physical characteristics(Borazon, Heino, & Glaser, 2023).studies suggest that identification of the whole stock of fish species is possible only by characterizing each species individually. For virtual identification of fish taxonomy, the ring-like growth patterns on fish are studied. These patterns determine the age of fish and its ecological background. in the present age of technology, a deep learning algorithm is used to classify fish species present in fish stock(Cayetano, Stransky, Birk, & Brey, 2024).studies explain that fish species found in freshwater lakes are a source of protein and nutrients for people who cannot afford high-quality fish protein sources.

The resemblance between different fish species makes the classification process difficult. using computerized vision tools based on an algorithmic approach helps classify fish species based on their appearance and morphological features(Deka, Laskar, & Baklial, 2023).Studies claim that certain fish species make a sound that is detected using acoustic sonars. These sonars catch the sound frequency of fish species and then interpret the sound to determine the taxonomy category of fish species making the sound.To detect several acoustic waves from different fish species, an acoustic imaging model based on a deep learning approach is preferred(Fernandez Garcia, Corpetti, Nevoux, Beaulaton, & Martignac, 2023). Researchers reveal that the fisheries present in aquaculture undergo image-based analysis to detect any deformity in the body of fish. This detection process is usually carried out for biomedical research purposes. Biomedical research on some physically ill fish species indicates the presence of toxins in the water(Kumar, Marée, Geurts, & Muller, 2023).Studies reveal that the detection of certain diadromous species, as well as angullium species, through acoustic cameras is a time-consuming process and is difficult to perform.to develop a time-saving computerized visualization technique for morphological studies (Le Quinio et al., 2023).studies suggest that automated monitoring systems in aquaculture help monitor the health status of fish species. the automated system detects the amount of feed given to the fish species. The fluctuations in the amount of fish feed result in the use of disease in fish species in aquaculture(Liu, Ma, Yu, Wang, & Hao, 2023). Studies conclude that images obtained from imaging analysis or monitoring systems are of poor quality and thus create confusion regarding the taxonomic background of fish species. Pré-processing tasks are used before image analysis to improve image quality. the processing is performed using algorithms that classify the deep sea and upper sea species(Lopez-Vazquez, Lopez-Guede, Chatzievangelou, & Aguzzi, 2023).to determine the biodiversity feature associated with fish species, it is important to study the ecological importance associated with fish species.To assess different morphological features of many fisheries,, the Fish-Visual Trait Analysis Database is used in studies (Mehrab et al., 2024).

Studies explain that classifying tuna fish through growth ring patterns on their skin is time-consuming. An automated system is preferred in China's fisheries centre to minimise the time required to classify tuna fish. The SVM algorithm is employed in an automated classification process to classify the *Thunus* species(Ou et al., 2023).Studies reveal that fish species that humans do not classify are classified using automated systems. the classification through an automated system is more reliable than the classification made by humans based on similarities in closely related fish species. For classifying cryptic species, deep learning algorithms are used in study-based experimentations(Pinho, Kaliontzopoulou, Ferreira, & Gama, 2023).scholars claim that the Amazon fishery system is the largest acoustic ecosystem in the world. Identifying taxonomically distinct species in the Amazon ecosystem requires exceptional technology systems. imaging analysis tool based on deep learning algorithmic provides data about the molecular level identification of fish species(Robillard et al., 2023).studies claim that farmed fishes are monitored through automated systems to understand the growing patterns and breeding patterns in fish species. Sometimes, growth abnormalities are observed in farmed fish using deep learning technology-based monitoring systems(Saleh, Jones, Jerry, & Azghadi, 2023).Scholar studies show that the management process of coastal fisheries uses AI-based monitoring systems. in the Pacific Ocean, the species present in the coastal area are analyzed by visualizing cloud computing software (Shedrawi et al., 2024).studies emphasize the need to improve fishers' activities to improve the living conditions for fishermen. the most important thing that helps the fisherman in catching fish is knowing about the zones that are enriched with fish species.in modern areas of technology information about the fisheries zones is provided to the fisherman using automated systems(Sowmmiya, Roselyn, & Sundaravadivel, 2024).also, accuracy is required to detect the fish species for fish farming purposes.by studying the morphology of species, it becomes easier to farm fish species in aquaculture. the deep learning models provide fish aquaculture stakeholders with vital information about the specific freshwater and marine water fish species(Srivastava, 2023).Studies predict that fish species abundance in aquatic environments is possible using acoustic sensors as a technology tool. The data obtained from the acoustic sensor is interpreted using the deep learning algorithmic approach. moreover, the use of acoustic sensors provides great applications but certain limitations need to be overcome for studying the morphological traits of species without any hindrance(Yassir, Andaloussi, Ouchetto, Mamza, & Serghini, 2023).

Knowledge Concentration for Underwater Implanted and Superiority Processing

Fish monitoring applications typically utilize very big DL models with millions of parameters that need a lot of processing resources. To deploy these models on devices and in circumstances with limited resources, such as underwater monitoring stations, a variety of hardware-enabled compression methodologies, such as quantizing and binarising DNN, are utilized. Knowledge distillation is another approach that has received a lot of attention for condensing large-scale DL models. Knowledge distillation refers to the process of educating a student (a small network) to copy a teacher (a collection of networks). The primary idea is that the student model should be similar to the teacher model in order to perform competitively, if not better. The main issue, however, is passing on knowledge from a large instructor to a little student. Model compression was proposed by researchers as a method of accurately transferring knowledge from a large model to a smaller one. Furthermore, several alternative model compression approaches have been developed, and as a result of their potential, the community has grown increasingly interested in knowledge distillation. Applying knowledge distillation to embedded devices and underwater video processors provides a significant research opportunity for online and more efficient monitoring with high accuracy while utilizing limited resources. The limitations of data flow from underwater sensors and cameras, as well as the difficulty of underwater connection in the Internet of Underwater Things, make this particularly useful. To get an understanding of a marine biological system, it is crucial to observe the behaviour of several fish species. Numerous fish species' numbers and distributions can provide important information about the ecological system's health and serve as a gauge for tracking changes in the environment. A fuller understanding of the species as a whole may be gained by visually identifying fishes, which can also help track their movements and reveal patterns and trends in their activity. By automating the visual categorization process of fishes and obtaining visual input from various locations, it is possible to automate the study of fish behaviour. This will yield much more data for pattern identification. Fish classification in datasets generated from underwater recordings has not seen any notable advancements, despite several advancements in the classification of fish removed from the ocean or in artificial environments, such as tanks with sufficient lighting. Fish species categorization underwater is complicated by issues with noise, distortion, overlap, segmentation inaccuracy, and occlusion. Simpler methods like brightness are also limited by the complicated environment, and background removal involves problems including colour shifting, uneven illumination, the presence of sediments in the water, and swaying underwater vegetation.

Identification of fish species is a multi-class classification issue and an interesting area of computer vision and machine learning research. Modern algorithms that achieve classification primarily through the extraction and matching of shape and texture features are applied to individual input photos. All of the current research is either inaccurate or only uses a tiny dataset to discriminate between fewer species. Convolutional neural networks are used in our suggested approach, which simplifies and strengthens the procedure even when handling big datasets. Additionally, CNNs are far more adaptable and can change to accommodate new data as the dataset becomes older. To test our method, we utilize the Fish4Knowledge project's fish dataset. Gaussian Blurring, Morphological Operations, Otsu's Thresholding, and Pyramid Mean Shifting are used as pre-processing techniques to conduct the classification. The improved pictures are then sent into a Convolutional Neural Network for classification.

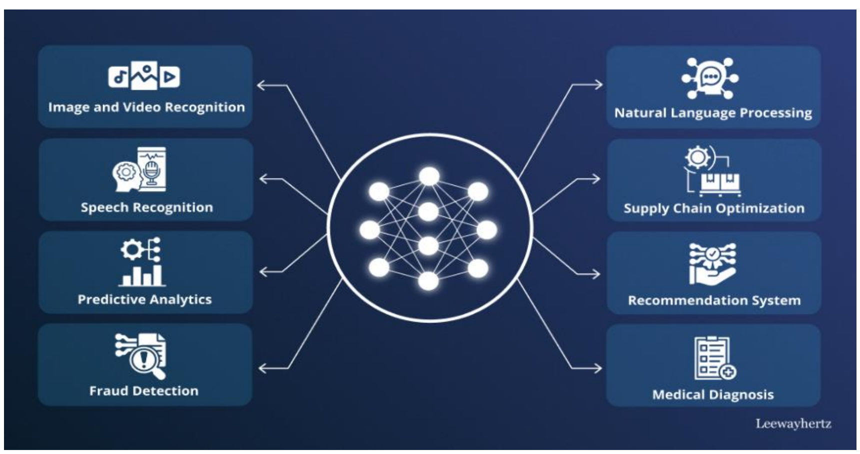

Figure 1: Deep learning for morphological analysis

How Deep Learning Fluctuates from Machine Learning

A collection of algorithms that can automatically create prediction models and identify patterns in data are usually referred to as machine learning (ML). Since deep learning (DL) makes use of the same kinds of data and learning techniques as machine learning (ML), it is categorised as a subclass of ML. However, in order to transform unstructured input—like text and images—into a structured framework for learning, machine learning usually requires some pre-processing. On the other hand, DL usually doesn't need as much data pre-processing as ML. By automating feature extraction, unstructured data recognition, and interpretation, it drastically reduces the requirement for human knowledge. For instance, ML has to explicitly supply some fish attributes (such size, shape, colour, and patterns) in terms of pixel patterns in order to identify fish in a picture. Because it frequently necessitates a strong understanding of the subject and exceptional programming abilities, non-ML specialists may find this difficult. DL methods, on the other hand, completely disregard this stage. DL systems can use general learning techniques to automatically identify and extract features from data. Accordingly, we only need to indicate to a deep learning algorithm whether a fish is present in an image; if we provide enough instances, the system will be able to identify the type of fish. By dividing the data into layers with different levels of abstraction, an independent learning approach is made possible, enabling the computer to recognise the characteristics that characterise the data. Deep learning algorithms may be able to identify the traits—like fishtail—that are most crucial for distinguishing one species from another. This feature hierarchy has to be manually created by an ML specialist before deep learning.

The deep learning procedure: The foundation of deep learning is made up of deep neural networks (DNNs), often referred to as artificial neural networks. To accurately recognise, categorise, and characterise objects in a given data set of interest, DNNs employ a range of data inputs, weights, and biases. A DNN's capacity to categorise or predict is enhanced and refined with each layer of connected nodes. UNET, a popular deep neural network architecture for image processing, is shown in Figure 5. In an input picture, UNET, a sophisticated deep learning architecture, aims to segment a fish's body. It is made up of several levels and parts. Three different types of layers make up each DNN: input, output, and hidden. Figure 6 displays the input and output layers. The final prediction or classification is made by the DL model in the output layer after the data has been received for processing at the input layer. Forward and backward propagation are the two main mechanisms via which learning takes place in a conventional neural network, including a DNN. a conclusion on classification or prediction. The mechanism by which learning takes place in the network is called backward propagation, or simply backpropagation. Using a training model that calculates prediction errors, backpropagation iterates over the layers of the neural network, changing its weights and biases. A neural network can reduce network flaws and generate predictions due to forward and backpropagation. With every cycle of backward and forward propagation, the neural network's classification or prediction accuracy increases. The concepts listed here are used by almost all DNNs. On the other hand, DL networks and designs address a number of issues. For instance, CNNs are capable of identifying traits and patterns in images, which enables them to do tasks like object identification and recognition. Speech recognition, natural language processing, and time-series forecasting are just a few of the many applications that frequently use recurrent neural networks (RNNs). Many DL approaches, despite their variations in design, make use of the idea of supervised learning to comprehend incoming data and complete various tasks.

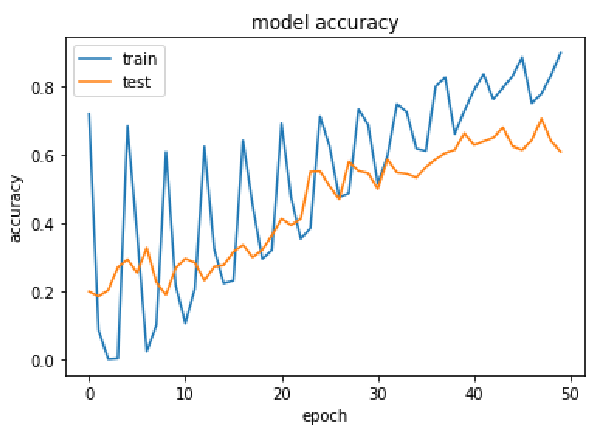

Figure 2: Model Accuracy

Deep Learning Gap: There are several ecological advantages to the new field of deep learning. The oldest and most evident ecological uses are the categorisation and counting of fish. Absolute abundance (fish per area or volume unit) and DL-predicted fish counts are still at odds. The use of CNNs to ecological issues like fish populations and species categorisation is the main focus of current DL literature. However, fish absolute abundance is important for ecological studies and species protection. An important topic in ecological studies is the dynamics of fish populations. One way to address this problem is to examine long-term data on fish migrations and populations. However, obtaining such long-term data sets is costly and uncommon. Extracting as much information as possible from the small amount of available data is therefore crucial. New approaches are needed to provide a reliable long-term assessment of fish densities or, better yet, an estimate of fish absolute abundance. Additional ecological topics that may be covered with DL include species habitat selection and the connection between the physical environment and life cycles. DL methods can assist us in this area as they may make use of all the information that is accessible. More sophisticated training methods, a deeper understanding of the issue domain, and a variety of network architectures might all raise the current state of DL research. The corpus of recent DL research indicates that far more innovative methods will be used in the future. Most of them still don't have enough evidence to demonstrate their superiority over current practices. However, there are certain practical uses, like classifying fish. For a range of ecological issues, a deep learning method can yield very precise estimates of fish densities or absolute abundance. However, it is unclear if this accuracy is exclusive to the appropriate approach or a feature of the training data set. According to this perspective, a significant ecological issue is creating a generic method for estimating fish densities and absolute abundance from limited data. Using DL models that have been trained on other data sets—as long as they are pertinent to the fish density/abundance problem—is one way to address this issue. The ecological literature suggests that there is probably a complicated relationship between a species' life cycle and its physical environment (e.g., fish density) because the physical environment varies from species to species. Consequently, there could be several comparable data sets on similar topics (e.g., engineering or environmental science). In addition to broad methods to estimate the absolute abundance of fish from very little data, it is critical to develop and assess generic techniques that may use ecological knowledge and domain-specific data from a given situation.

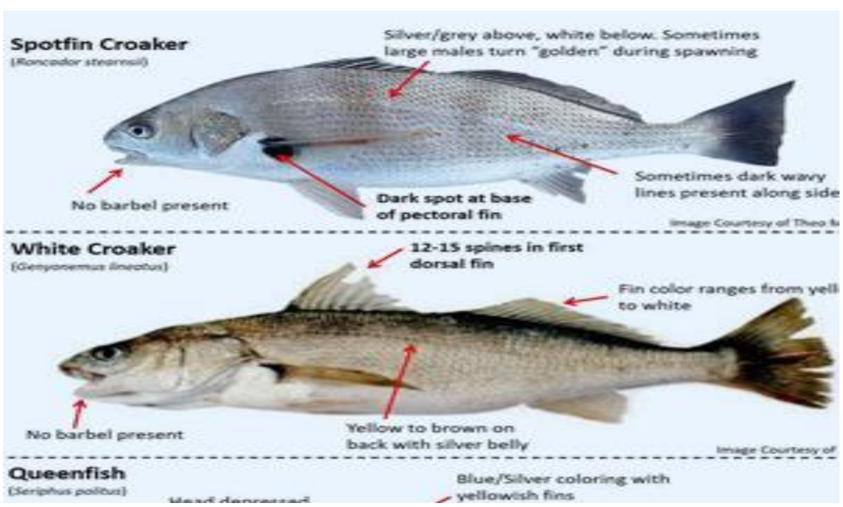

Figure 3: Fish species in large data bases

Deep learning for Morphology

One characteristic that sets all living things apart is their biological form, or morphology. Organs, tissues, and bodies are examples of morphological traits that are created during development and are subject to change throughout time. It is anticipated that morphological comparisons between humans and animals will provide details about the evolutionary and developmental history of shape as well as its practical significance. Since shape quantification and characterisation enable us to characterise, understand, and illustrate changes in form, they are essential for detecting such traits from morphology. Up until now, shape analysis has garnered a lot of interest, and many different approaches have been put out. The most popular kind of shape analysis is called landmark-based geometric morphometrics, in which the form of a particular sample is defined by the coordinates of landmarks, which are identified by anatomically comparable locations on several samples. Applications for this landmark-based method are numerous and include vertebrates, molluscs, plants, and arthropods. This approach has certain inherent ambiguities and limitations, despite its widespread use. The landmark-based method is ineffective for comparisons between phylogenetically distant species or distant developmental stages (e.g., between the early and late stages) where biologically homologous landmarks cannot be defined. This is in contrast to interspecies comparisons between close species or near developmental stages, which have revealed morphological changes through evolutionary or developmental trajectories.

Second, both a big and small number of landmarks may cause information about the morphology of a sample to be lost. Inaccurate landmark configurations created by researchers due to skill level discrepancies and errors produced by measuring tools might also be an issue. A landmark-free technique for characterising the morphology of cells, bivalves, fish, and plant components is elliptic Fourier analysis, or EFA. The landmark-based approach, also known as EFA, and principal component analysis (PCA) are frequently used to reduce the high-dimensionality of morphological data to an easily visualised low-dimensional space. While linear techniques that reduce dimensionality, such PCA and linear discriminant analysis (LDA), are easy to apply, nonlinear alternatives, like deep neural networks (DNNs), may be helpful for capturing more complicated features in fewer dimensions. DNN-based nonlinear algorithms have been applied sparingly in morphological analysis, especially morphology feature extraction, despite being utilised in image classification and medical diagnostic imaging. The analysis is sometimes black-boxed and hard to understand, which might be a drawback of the DNN approach, despite several attempts to address this problem. In order to evaluate form from picture data, this work proposes a landmark-free method based on variational autoencoders (VAE) that does not require explicit landmark annotation. An encoder plus a decoder make up a VAE, a type of DNN. The decoder uses the compressed latent variables to rebuild the input picture after the encoder has transformed high-dimensional image data into low-dimensional latent variables. Because of the encoder's nonlinear data compressibility, VAE is able to extract features from picture data. Instead of compressing the input image irreversibly, the VAE decoder's reconstruction capabilities make sure that no information is lost during the compression process. We can extract morphological characteristics that are most effective at differentiating data between distinct labelled groups by including a classifier module into the original VAE. This work is the first to employ a hybrid architecture in morphometrics, despite earlier suggestions for similar structures that combine supervised and unsupervised learning.

Summary and Conclusion

Apart from simplifying the application of DL to practical issues in fish-related marine research, this article aimed to give scholars and professionals a summary of the current uses of DL in fish visual monitoring under water. The technique known as DL has developed into one that can offer hitherto undiscovered advantages to a number of fish habitat monitoring and marine research applications. In the ideal world, DL will be extensively utilised in marine habitat monitoring for two reasons: (1) to enhance the calibre of automated monitoring instruments by means of data gathering and feature extraction, and (2) to offer a dependable method of surveying fish habitats and comprehending their dynamics, in tandem with a plethora of other developments in monitoring hardware and underwater communication technologies. Future monitoring initiatives should be able to improve the efficacy of marine ecosystems study by practitioners and researchers. Our efforts in data collecting, model building, and deployment will need to be concentrated and coordinated in order to achieve this. Clear and repeatable research data and tools are also necessary to help us reach our objective more quickly. At the cutting edge of machine learning technology, deep learning (DL) offers the processing capacity required to fulfil underwater video's potential as a vital tool for fish visual sampling. Significant species similarities, fish occlusions, cluttered backdrops, and adverse water conditions have all contributed to the spatiotemporal consistency of underwater video quality. It provides precise and efficient solutions for a range of challenges. Because of this, DL makes it possible for underwater video to facilitate thorough fish sampling, particularly when combined with other advancements in underwater communication and monitoring devices. The formerly unachievable objective of creating a comprehensive comparative understanding of aquatic and marine fish species and ecosystems may now be achieved since this can extend from shallow freshwater and marine environments to the deep ocean. Most importantly, DL solves the problem of consistently and effectively handling the massive amounts of data produced by underwater video, turning a costly endeavour into a straightforward computer processing task. Deep learning enables processing large amounts of data, which might lead to unprecedented levels of spatial and temporal replication in underwater fish video surveys. Underwater films that are simultaneously deployed over various habitats at multiple geographical scales or that provide continuous data throughout time allow for enormous advances in knowledge. Deep learning and related techniques could be widely applied in marine habitat monitoring to either (1) enhance the quality of automatic monitoring tools by classifying data and extracting features, or (2) offer a dependable way to survey fish habitats and comprehend the dynamics of their movement. Focused and coordinated efforts in data collection, model construction, and model deployment are necessary for effective DL development. Transparent and reproducible research data and technology that enable us to accomplish our goal more quickly are also necessary. Researchers and practitioners studying marine ecosystems would benefit from this by being able to improve the efficacy of their monitoring activities. In many sectors, including industry and agriculture, classifying fish is a crucial task. We suggested a deep learning approach in this study to learn pictures of nine distinct fish species from the Kaggle website. We enhanced the CNN model VGG16 that had already been trained. After training and testing the suggested model, we assessed its performance using an unidentified dataset in this work. Our accuracy rate, precision, recall, and f1-score were all 99.68%, 99.69%, and 99.68%, respectively. This indicates that our suggested approach may accurately classify and forecast various fish species.

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