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Exploring Fish Species Classification Using Deep Learning

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Abstract:

Fishes are intriguing creatures that live in a wide range of aquatic settings, including freshwater rivers and lakes, oceans, and deep-sea trenches. Freshwater fish are considered a poor man's protein supplement since they are readily available in lakes, rivers, natural ponds, rice fields, beels, and fisheries. Many freshwater fish species resemble one another, making it difficult to classify them based on their exterior appearance. Manual fish species identification is always error-prone since it requires knowledge. Recently, computer vision and deep learning have played a key role in underwater species classification and detection studies. This research focuses on fish species categorization with Convolutional Neural Networks (CNNs).The objective of this research is to develop an automated system capable of accurately identifying and categorizing various fish species using a dataset. The study entailed optimizing the ResNet50 and VGG16 architectures and employing a Convolutional Neural Network (CNN) to train and validate the acquired fish data. The proposed approach involves performing preprocessing on the image data, training the CNN models using the ResNet50 and VGG16 architectures, and evaluating their performance using metrics such as accuracy, precision, recall, and F1 score. The study demonstrates that the classifier is highly efficient, with an accuracy, precision, and recall rate of approximately 95%. However, it also demonstrates that boosting the learning rate to make the model learn faster might actually lead to a drop in its performance on fresh data.

Keywords*: Classification, Convolutional Neural Network (CNN), VGG16, Rest Net 50*

1. INTRODUCTION

Fish species classification is critical in the domains of aquatic research, marine, biodiversity and in education. Conservation, and fishery management. Accurate identification of fish species is critical for understanding biodiversity, monitoring population dynamics, and implementing successful conservation initiatives. Traditional species identification methods are based on manual observation and skill, which can be time-consuming and error-prone. With advances in deep learning and computer vision, automated systems based on Convolutional Neural Networks (CNNs) have emerged as effective tools for image-based classification tasks. The objective of this project is to enhance the efficiency of a Convolutional Neural Network (CNN) model used for identifying and categorizing fish species. The study specifically concentrates on developing a fish species classification system using two well-known CNN architectures, ResNet50 and VGG16. These architectures are renowned for their exceptional performance in tasks related to image identification and are commonly employed as benchmarks in deep learning research. The integration of a universal artificial intelligence system for all species, along with conflict categorization models, has resulted in a hierarchical decision-making process that has shown improved performance [2][6][10]. This work demonstrates the efficacy of deep learning algorithms in automating the identification of fish species through thorough testing and analysis. Additionally, it plays a role in advancing aquatic research and supporting conservation endeavors.

A. Challenges in the Accurate Identification and Classification of Fish Species

There are a few significant challenges to correctly identifying and classifying fish species. Figure 1 illustrates these challenges. To address these challenges, experts in fish picture recognition are developing advanced machine-learning models and improving data collection and annotation techniques. The variable look of fish species, which is impacted by factors such as size, color, and environmental conditions, makes it difficult to develop a strong model capable of reliably classifying multiple visual traits. Obtaining a sufficiently large and diverse dataset for training deep learning models can be difficult [6], particularly for uncommon or endangered species, which could contribute to performance biases. Some fish species might have similar visual characteristics, making it difficult for the model to distinguish between closely related species based just on visual attributes. Adaptation to New Species. The model's adaptability to previously unknown or newly found fish species is critical for its practical application in varied ecosystems, and it may necessitate additional mechanisms for continuous learning.

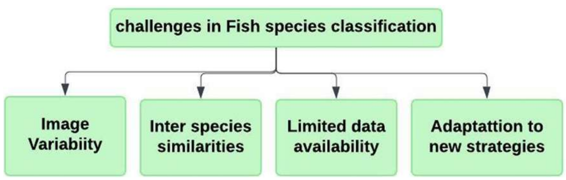


Figure 1. Challenges Fish species identification

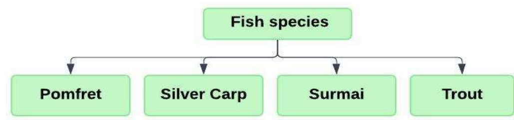


Figure 2. Types of Fish Species

B. Type of Species

Pomfrets are a group of fish species known for their silver-colored bodies, flat shape, and delicate flavor, making them popular in various cuisines worldwide. Tuna are large, fast-swimming fish prized for their firm flesh and rich flavor, making them a staple in seafood dishes and a valuable commodity in the fishing industry. Surami, also known as King mackerel, are saltwater fish characterized by their elongated bodies, silvery scales, and strong flavor, often enjoyed grilled or in curries. Silver carp are freshwater fish known for their silver-colored scales and leaping behavior when startled, commonly used in Asian cuisine for their mild taste and versatility in cooking. Figure 2 shows numerous fish species types, each with unique characteristics and adaptations.

C. Research Contribution

This section summarizes the contributions of the current research article, including a comprehensive review of the existing literature on classifier performance and learning rates. It summarizes recent advances in deep learning algorithms for fish species classification. The study covers research from 2018 to 2023, offering a full overview of cutting-edge methodologies and approaches in the sector. The literature has examined a variety of datasets and methods for detecting fish species. The primary focus of this study involves employing Deep Learning techniques, specifically convolutional neural network architectures like VGG16, to detect and categorize various fish species. These architectural models, particularly their layers [20], play a crucial role in identifying key features essential for accurate fish species classification. It underscores the importance of deep learning in addressing intricate challenges related to fish species identification through the application of Deep Learning and sophisticated architectural models. The methodology utilizes deep learning algorithms to effectively detect and classify fish species depicted in images. It has the potential to contribute significantly to the development of sustainable disease management strategies in the field of agriculture. The research contribution is to extend beyond conventional fish species classification methods by incorporating advanced techniques, temporal analysis, and adaptability features. These advancements have the potential to significantly impact ecological studies, fisheries management, and environmental conservation efforts. The proposed method will aid in the precise classification of carp and tiny indigenous fish species raised in a ploy-culture setting. The planned work will also assist many stakeholders in fisheries, including government officials, policymakers, scientists, and farmers, in creating efficient conservation methods for these freshwater fish species for stock management.

D. Research Question

Some research questions of the study are.

- How does the accuracy of deep learning algorithms for fish species identification compare to traditional methods?
- What are the key factors affecting the accuracy of deep learning algorithms in classifying fish species?
- How can integrating data from various sources enhance the accuracy of fish species classification and identification?
- In what ways can early detection and accurate classification of fish species support local fish farmers in mixed culture farming to achieve optimal growth and increased production?

II. LITERATURE REVIEW

Limited efforts have been made to identify fish species from image datasets of fish, despite the fact that several researches have been completed on the identification of diseases from image datasets using deep learning and convolution neural network-based methods. A study of the literature looks at the approaches currently used for picture classification utilizing transfer learning techniques. The objective of this work [1] is to enhance the efficiency of a YOLO model for the identification and categorization of fish. The integration of global (a single artificial intelligence for all species) [2] and disagreement categorization models resulted in a hierarchical decision-making process, leading to improved performance. The detection of unhealthy fish is greatly challenged by the presence of low-quality underwater images and targets that are difficult to identify [3]. This research presents a model for detecting unhealthy fish in aquaculture by utilizing an enhanced YOLO network, aiming to address the aforementioned issues. The proposed approach [4] achieves an impressive 96.29% classification accuracy for fish species by utilizing Convolutional Neural Networks, Deep Learning, and Image Processing. An impressive 94.44% accuracy was obtained [5] when Convolutional Neural Networks (CNN) were used to detect fish diseases. The author in [6] talks about the potential of CNN's as a quick and efficient method to diagnose fish illnesses, with encouraging overall performance metrics. As a result, an inventive smartphone application has been created for this research to identify fish species that are frequently found in Mauritius's lagoons, coastal regions, estuaries, and outer reef zones. This investigation [7] provides two effective methods: Deep Convolutional Neural Network techniques for precisely recognizing living fish in underwater footage. This work [10] proposes that managing ecosystems requires an understanding of fish species. The solution treats it as object detection in a photo and makes use of MobileNetv3-large and VGG16 with SSD. To handle unusual species, researchers have devised a revolutionary method that enhances system concentration. The accuracy of the updated model improved by as much as 79.7%. In this [11], the author introduces a novel approach based on convolutional neural networks (CNNs) for the recognition of Pantanal fish species. The method involves a newly devised CNN comprising three branches tasked with classifying fish species, family, and order. The objective is to enhance species recognition, particularly for species with similar characteristics. The author in [12] showcases the ResNet-50 model achieving the highest overall classification accuracy, precision, and recall rate of 100% at a learning rate of 0.001, as evaluated on both the custom dataset and the benchmark Fish-Pak dataset. Extensive empirical analysis demonstrates that increasing the learning rate of Weight and Bias leads to higher validation loss incurred by the classifier [13]. This research proposes fish species classification in images using transfer learning with MATLAB as an initial step in addressing this problem. This investigation [14] highlights the challenge posed by the limited availability of large datasets for deep neural network applications, which we address through transfer learning techniques [15]. The article in [16] focused on fish image classification, acknowledging the apparent simplicity yet complexity of the process. Recognizing the importance of scientific research on population counts and geographical behavior, the researchers employed advanced computer vision and data mining techniques. The research [17] addresses the need for an automated fish species classification system, highlighting the limitations of traditional labor-intensive methods in underwater environments. This [18] new approach introduces a smartphone app for fish species identification in Mauritius, utilizing a dataset of 1520 images across 38 species. Preprocessing involved Gaussian blur and thresholding. Among classifiers tested, KNN achieved 96% accuracy, and a Tensor Flow model reached 98%.

This study [19] introduces an efficient fish species classification system for aquatic images, crucial for ecological and conservation purposes. Utilizing an enhanced auto encoder-decoder with improved feature selection through gray wolf optimization (EGWO), the proposed method outperforms established deep learning models (Alex Net, ResNet, VGG Net, and CNN). The author in [20] talks about overfishing by introducing a novel image-based method for detecting individual fish in commercial trawling. Using stereo images from the Deep Vision system within the trawl, the proposed approach employs Mask R-CNN for precise fish localization and segmentation. This study [21] presents a unified approach using image processing and machine learning for non-invasive monitoring of fish morphological features in aquaculture. Innovative techniques, including edge and corner detection, estimate fish length, height, and area in images. Tested on 25 photographs per species for four popular fish species, the method shows estimation errors between 1.9% and 13.2%. This work [22] explores fish image classification in ichthyology, comparing convolutional neural networks (CNNs) such as Alex Net Google Net, and ResNet. The CNNs, trained with transfer learning and data augmentation on an 18,000-image dataset, achieved high accuracy (Alex Net 99.85%, Google Net 96.39%, ResNet-50 99.51%). This work [23] introduces IsVoNet8, a convolutional neural network for classifying 8 fish species from 6 families, including widely consumed marine fish in Turkey. This study [24] focuses on the crucial task of accurately classifying fish species, proposing the Chaotic Oppositional Based Whale Optimization Algorithm (CO-WOA) within an enhanced deep learning framework. The proposed method, utilizing the Proposed Deep Learning Model. Automated fish identification [25] is crucial since the process of identifying fish species is still difficult and time-consuming. As a type of machine learning [26], deep learning produces precise outcomes by mimicking human instincts of learning by doing. The rapid adoption of deep learning [27] in aquaculture has opened new possibilities and challenges. This paper reviews DL applications in smart fish farming, covering live fish identification, species classification, behavioral analysis, feeding decisions, size estimation, and water quality prediction. In this [28] author discusses the world's dependence on seafood and the harm that illicit fishing practices do to the marine ecosystem. Feature extraction and analysis are carried out by Convolutional Neural Networks (CNNs), which achieve 90% and 92% detection and classification accuracy, respectively. This work aims [29]to provide a method for the automated classification of fish species. For marine biologists and Ichthyologists to better understand fish behavior, a high degree of precision in fish classification is necessary. In order to evaluate marine species [30] without causing damage, underwater cameras are being utilized more and more in marine research. Interest in automatic fish classification has arisen from the time-consuming nature of the manual study of fish pictures. The proposed method in this [31] improves object classification and counting in underwater videos by accumulating past frame data. It achieves high classification probabilities for Bluegill (93.94%) and Largemouth bass (97.06%), showing strong performance in underwater environments [32] Using customized datasets. This [35] utilized YOLOv4 with lightweight convolution to develop a fish skin disease detection model. It is used for real-time monitoring in deep-sea aquaculture and has been tested on a variety of diseases. The model performs faster and more accurately than the original YOLOv4. This study [37] develops a fish species classification system using YOLO architecture, achieving 92% accuracy [38] in the study presents a two-step deep learning method for detecting and classifying temperate water fishes from underwater images. Transfer learning boosts accuracy, achieving 99.27% in pre-training and good precision values in post-training. It [39] proposes an improved YOLO-V4 network for real-time detection of uneaten feed pellets in aquaculture. This endeavors [40] proposes FD_Net, based on improved YOLOv7, for detecting nine fish species with a 14.29% higher map than YOLOv7. FD_Net achieves superior performance in complex underwater environments compared to other models.

This study [41] examines the advantages and disadvantages of various diagnostic techniques in various settings while providing a thorough evaluation of image-processing technologies and image-based fish disease detection techniques. It [42] uses innovative machine learning techniques to quickly identify and forecast deterioration in water quality. The strategy is to enable farmers to take preventative action against certain diseases that affect fish. Large-scale fish illnesses occur often in aquaculture [43], which highlights the need for rapid, non-destructive, automated disease prediction. Utilizing high-resolution cameras and image processing technology, fish health and safety are ensured by early disease detection and control. Fish illnesses cause a high death rate. While early detection is essential, expertise is frequently needed [44]. In order to a fish infections are promptly detected and classified using a Probabilistic Neural Network (PNN), which aids farmers in making defensible judgments and averting widespread fish mortality [45]. This study [46] examines image-based techniques for detecting fish diseases and emphasizes the need for increased speed and accuracy. For marine insights, tracking fish species [47] and distribution is essential. Underwater Image Enhancement and Morphological treatments are used to overcome issues with underwater images, such as orientation shifts. In farms, fish illnesses cause a high death rate [48]. While early detection is essential, expertise is frequently needed. The field of artificial intelligence [49,57] particularly that of neural networks and convolutional neural networks, or CNNs has grown in popularity. With the improvements suggested in this research [50] , deep-learning algorithms such as MobileNetV2 achieve an average validation accuracy of 99.83%. This makes it possible to classify marine species in fisheries effectively on the spot, which helps with ecosystem management [51]. Research on fish classification and recognition tasks started back in the year 1993

III. GAP ANALYSIS

Although previous research on fish species prediction has been undertaken, the purpose of this study is to find gaps by analyzing existing efforts. It delivers findings in a tabular manner, setting itself apart by providing a full review of essential features incorporated into 'fish species classification. Table 1 provides a complete review of these characteristics, emphasizing their design for improved user experience and functionality. It describes the application's capabilities, such as fish prediction and recognition using computer vision. Each feature in Table 1 is briefly discussed, highlighting its significance in the application's ecology. This table provides insight into the various functions of fish species classification. Table 2 highlights the top 36 research publications reviewed for information on fish species classification. Table 3 serves as a mapping of sources.

A. Feature Table

Many research articles were reviewed to improve research work, and a list of features that had been examined to classify fish species was given. Table 1 describes many features collected from the previous literature paper and their summary. It displays several valuable works and features in a precise manner.

*B. Source Tabl*e

Table 2 lists eight of the many functional and useful research papers that have been read and observed to gain knowledge for classification performance before proposing methods of classifying fish species using deep learning.

*C. Source and Feature Combine Comparison Tabl*e

Table 3 displays the consolidated results in tabular form for the association between the research papers and the features outlined previously. It also assists in deciding what characteristics this research possesses. It compares and contrasts this research work with various elements of different research articles to demonstrate trends, patterns, and relationships between study findings. In recent years, significant strides have been made in the field of fish species detection, thanks to the integration of both ML (machine learning) and DL (Deep learning) techniques. These cutting-edge technologies have revolutionized the ability to accurately and efficiently identify and categorize fish species. Traditionally, manually engineered features have been utilized for feature extraction and classification in fish species detection. However, a subset of Deep Learning algorithms known as Convolutional Neural Networks (CNNs), VGG16 and ResNET50 have shown remarkable potential for autonomously acquiring hierarchical representations from raw data, such as image files of fish. Comparing these algorithms with earlier research in Table 4, it's evident that there's immense potential for ecological monitoring, conservation initiatives, and scientific research when leveraging cutting-edge technologies for fish species detection.

IV. COMPARISON WITH STATE OF ART

The materials and techniques need to be comprehensive so that other researchers can build on previously published findings and repeat them. While well-established methods can be quickly presented and properly cited, new methods and protocols should be described in detail. Provide the software's name and version, and indicate if the computer code was accessed. Incorporate any codes for pre-registration.

Table 1. Feature Table

F#	Name	Description
F1	Machine Learning	A concept of machine learning is being used or implemented in the paper's research methodology
F2	Dataset	Dataset is being used by the application for training
F3	Deep learning	Deep learning is used in the research paper methodology
F4	Image	Application is working on and image's dataset
F5	Mobile Application	Application is working on and image's dataset
F6	Disease identification	Determine if the fish have disease or not.
F7	Camera	The application uses the camera for input.
F8	User Interface	Intuitive and user-friendly interfaces for users to interact with the software, review results.
F9	Size Recognition	Recognition of distinctive size associated with dead fish.
F10	Transfer Learning	Use features extracted from pre-trained models on related tasks (e.g., marine life recognition) to enhance performance.
F11	Updates Maintenance	Regular updates and maintenance to incorporate improvements, address bugs, and adapt to changes in fish populations or environmental conditions.
F12	Scalability	Scalable architecture to handle large datasets and adapt to different deployment scenarios, from small-scale projects to large-scale fisheries monitoring.
F13	Security & Privacy	Secure user accounts and data.
F14	Offline Capability and Storage	Allow users to store and categorize images offline.
F15	CNN Algorithm	In order to identify fish species, the paper uses the CNN algorithm.
F16	Computer Vision Model	To ensure that the model is robust, gather a varied data set of fishes with species annotations, taking care to ensure that the less, lighting, and backgrounds vary.
F17	KNN Algorithm	The KNN method is used in this research to extract relevant characteristics from image data that describe different fish species.
F18	VGG16 Algorithm	Approaching the VGG16 algorithm in paper Accumulates a tagged dataset of fish photos with species annotations.
F19	YOLO Algorithm	The YOLO technique is used in this paper to gather and categorize a dataset of fish photos, complete with bounding boxes surrounding each fish and species information.
F20	Multi-Species Recognition	Support for identifying and classifying multiple fish species simultaneously.
F21	Resnet-50	A deep convolutional neural network architecture used for image classification and feature extraction in computer vision tasks.

Table 2. Source Table

S1	[1] Improved Deep learning Model for underwater species recognition in aquaculture.
S2	[3] Diseased fish detection in the underwater environment using an improved. YOLOV5 network for intensive aquaculture.
S3	[4] Underwater fish species classification using convolutional neural networks and deep learning.
S4	[5] Fish disease detection using convolutional neural networks (CNN).
S5	[7] Data augmentation and hierarchical classification with deep learning for fish species identification in underwater images
S6	[8] Temperate fish detection and classification a deep learning-based approach
S7	[10] Class-aware fish species recognition using deep learning for an imbalance dataset
S8	[11] Improving Pantanal fish species recognition through taxonomic ranks in convolutional neural networks, ecological informatics
S9	[14] Fish species recognition using transfer learning techniques
S10	[15] Acoustic fish species identification using deep learning and machine learning algorithms
S11	[16] Image processing model with deep learning approach for fish species classification
S12	[17] Transfer learning-based fish species classification model
S13	[18] A mobile application for fish species recognition using image processing techniques and deep learning
S14	[20] Application of machine learning and artificial intelligence in marine science
S15	[22] Convolutional neural network architecture performance evaluation for fish species classification
S16	[24] Novel optimization approach for deep learning classification of fish image
S17	[26] Survey on evolving deep learning neural network architecture
S18	[27] Deep learning for smart fish farming applications, opportunities and challenges
S19	[28] Classification of fish species using multispectral data from a low-cost camera and machine learning
S20	[30] Fish species classification in unconstrained underwater environments based on deep learning

Table 3. Sources and Features Table

F1	N	N	N	N	N	N	N	Y	Y	N	Y	N	N	Y	N	Y	Y	Y	Y	Y	Y
F2	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	N		Y
F3	Y	N	Y	N	Y	Y	Y	Y	Y	Y	N	Y	N	Y	N	Y	N	Y	N	Y	Y
F4	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	N	Y	Y	Y	Y	N	Y	Y	Y	Y
F5	N	N	N	N	N	N	N	N	N	N	N	N	N	Y	N	Y	N	N	N	N	Y
F6	N	Y	N	Y	N	N	N	N	N	N	N	N	N	Y	N	N	N	N	N	N	Y
F7	Y	Y	N	N	Y	N	Y	N	N	Y	N	N	N	Y	Y	N	N	N	Y	N	Y
F8	N	N	N	N	N	N	N	N	N	Y	N	Y	N	Y	N	N	N	N	N	N	Y
F9	Y	N	N	N	N	N	N	N	N	Y	N	N	Y	Y	N	Y	N	Y	N	N	N
F10	N	N	N	N	Y	N	N	N	Y	N	N	N	Y	Y	N	N	N	N	N	N	N
F11	Y	N	N	N	N	N	N	N	N	Y	N	N	N	Y	N	N	N	N	N	N	Y
F12	N	Y	Y	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	Y
F13	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	Y
F14	N	N	N	N	N	N	N	N	N	N	N	N	N	Y	N	N	N	N	N	N	Y
F15	N	N	Y	Y	Y	Y	N	Y	Y	N	N	Y	N	Y	Y	Y	N	Y	N	Y	Y
F16	N	N	Y	N	N	N	Y	N	N	N	N	Y	Y	Y	Y	Y	Y	N	N	N	Y
F17	N	N	N	N	N	N	N	N	N	N	N	N	Y	N	N	N	N	N	Y	Y	Y
F18	N	N	N	N	N	N	Y	N	N	N	N	N	N	Y	N	Y	N	N	N	N	N
F19	N	Y	N	N	N	Y	N	N	N	N	N	N	N	N	N	N	N	N	N	N	Y
F20	Y	Y	N	N	Y	N	Y	Y	Y	Y	Y	N	N	Y	Y	Y	N	N	Y	Y	Y

Table 4. Comparison table with previous studies

R#	Objective	Algorithm	Dataset	Metric	Accuracy	Year	Comments
[1]	To Develop an Effective Fish Detection Model Based on an Enhanced YOLO V5 Architecture.	YOLO	Car mask Dataset (Kaggle)	Precision, Recall and Map50	80%	2023	To Apply Computer Vision to Identify Fish Diseases in Real Time
[3]	This Study Aims to Present DFYOLO, A Fish Health Detection Network Built on Top of YOLOV5m.	YOLO	Dataset Collected In The Aquaculture Base Of Xian Ning Academy Of Agricultural Science, Hubei Province	Precision (P) , Recall (R) And Map	99.75%	2023	DFYOLO Network Based on YOLOV5m, To Detect the Diseased Fish In The Shoal Of Fish
[4]	Fish Species Classification System That Outperforms Existing Approaches with a High Accuracy Of 96.29%	CNN Convolutio nal Neural network	Fish4 Knowledge	Accuracy	96.29%	2021	Image Enhancement Techniques to Compensate for The Lost Features
[5]	The Goal of This Work Is to Diagnose Fish Diseases with an Amazing 94.44% Accuracy by Employing Convolutional Neural Networks	CNN Convolutio nal Neural network	Fish4 Knowledge	Precision (P), Recall (R) And F1-Score	92%	2022	Smartphone Application with CNN Model for Diagnosing Fish Diseases While On The Go.
[7]	CNN Techniques for Underwater Live Fish Recognition Are Presented Using Resnet-50.	CNN	Life clef 2015	Precision (P), Accuracy	99.86%	2020	Automated system that can classify fish species when a lot of different fish species are present.
[8]	Deep Learning Methodology Is a Formidable Instrument for Automated Fish Species Identification.	YOLO, CNN	Fish4 Knowledge	Confusion Matrix	99.27%	2020	Deep Learning Method for The Automated Analysis of Fish Species.
[11]	The Article Presents A Novel Approach For Species Recognition Of L fish Using Convolutional Neural Networks (CNN's)	CNN Convolutio nal Neural network	Dataset Collect from Pantanal Fish Species	Not Mentioned	96%	2019	In This Paper, An Innovative Method To Fish Species Recognition Via Convolutional Neural Networks Is Presented
[17]	The Work Aims to Provide a Productive Substitute for The Manual Identification of Fish Species by Marine Specialists in Order to Track Fish Biodiversity in Their Native Environments.	Convolutio nal Neural network (CNN)	Fish4 Knowledge	Precision (P) , Recall (R) , F1-Score And Kappa Score	98.03%	2020	Assesses Species Richness, Stock Size, And Ecosystem Health in Addition To Monitoring Fish Biodiversity.
[20]	The Study's Goal Is to Reduce Overfishing By Introducing An Image-Based Technique For Identifying Individual Fish In Commercial Trawling.	R-CNN	Annotated Images Was Acquire By RV	Precision (P), Recall (R) , F1-Score And Accuracy	79%	2019	Future Plans Call For Testing Precise Fish Shape Replicas Or Fish Specimens With Known Dimensions.
[22]	The Goal of The Study Illustrates Their Potential for Precise Fish Classification.	CNN	Dataset Collect Through Google Search Engine and QUT Fish	Confusion Matrix	99.85%	2021	Transfer learning is good for fast fish species identification.
[28]	The Main Objective Is to Categorize Spectra Of Tiny Fish Neighborhoods And Estimate The Percentage Of Each Species By Combining A Learned Classification Algorithm	Machine Learning Algorithm	Image Net, Fish4Knowledge	Precision (P) , Recall (R), Accuracy And Speed	63.8%.	2009	Working On R-CNN To Improve Outcomes In the detection and classification stages are included in the future scope.

Table 5. Dataset Description

Dataset break	Details of dataset
Total	20,527
Test	614
Train	19,913
Size	250*250*3
Type	JPG
Classes	106

The structure of a dataset used for image classification is described in Table 5. And dataset visualization is shown in Figure 3. There are 20,527 images in all, 614 of which are used for testing and 19,913 for training. Each image is saved in JPG format and includes three RGB color channels with a pixel size of 250x250. The dataset is appropriate for multi-class classification tasks because it has 106 different classes.

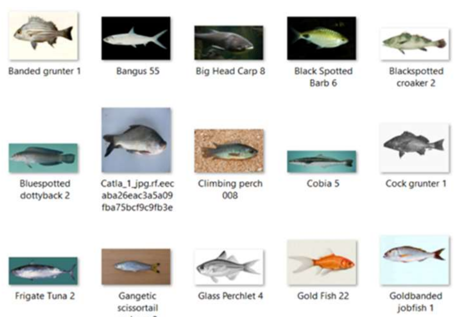


Figure 3. Dataset Visualization (106 species)

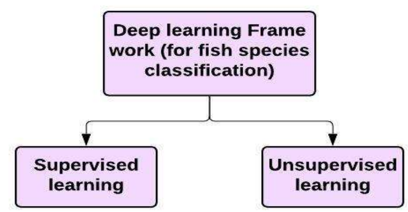


Figure 4. Deep learning types

A. Deep Learning Models

This research focuses on developing a Deep Learning Model for accurately detecting various types of fish, as shown in Figure 3. Convolutional Neural Network (CNN) architectures are employed, specifically VGG16 in Figure 6 and ResNet50 in Figure 7. A reliable dataset from Kaggle, containing numerous fish images, is used to train and test the fish image classification system. To ensure adequate variation for training, the dataset undergoes preprocessing and augmentation. After preprocessing, the dataset is divided into training and test sets. Deep learning models, particularly CNNs, are the leading approach for AI tasks involving large datasets and have significantly advanced computer vision and image classification. This work introduces a promising DL-based model for classifying fish species. The CNN architecture forms the basis of the deep learning model for fish image classification, as detailed below. The model's performance is evaluated using the test set, with the top-performing model identified based on validation set accuracy. Evaluation metrics include the F1 score, recall, accuracy, and precision. Additionally, the accompanying Figure 4 depicts a deep learning framework for fish species classification, highlighting two primary approaches: supervised learning and unsupervised learning. In supervised learning, the model is trained with a labelled dataset where each fish image is tagged with a specific species label. This enables the model to predict the species of new, unseen fish images. This study focuses on developing a Deep Learning Model for accurately detecting various types of fish. Convolutional neural Network (CNN) architectures, specifically VGG16 and ResNet50, are employed. A reliable dataset from Kaggle, containing numerous fish images, is used to train and test the fish image classification system. To ensure adequate variation for training, the dataset undergoes preprocessing and augmentation. After preprocessing, the dataset is divided into training and test sets. Deep learning models, particularly CNNs, are the leading approach for AI tasks involving large datasets and have significantly advanced computer vision and image classification. This work introduces a promising DL-based model for classifying fish species. The CNN architecture forms the basis of the deep learning model for fish image classification, as detailed below. Conversely, unsupervised learning does not use labelled data but seeks to discover natural structures in fish images by clustering them based on visual or other inherent features without predefined categories. This can reveal patterns or similarities, potentially leading to the discovery of new species or a better understanding of variations within known species. In this study, supervised learning components of the deep learning framework for effective fish species classification.

B. Convolutional Neural Network

Convolutional Neural Networks (CNNs) are a specialized type of neural network [20] designed for grid-like data, such as images or videos, as shown in the overall structure in Figure 5. These networks are particularly effective at extracting hierarchical features and are widely used for image processing, object detection, and pattern recognition tasks. The core of CNNs is convolutional layers, where filters slide over input data (like an image) to perform mathematical convolutions, identifying edges, textures, and other features. CNNs typically start with an input layer that processes images, followed by convolutional layers that extract basic to complex patterns. These patterns are refined through pooling and fully connected layers, leading to a final prediction using a Soft Max layer for multi-class classification. The network learns and updates its weights via backpropagation, optimizing accuracy for tasks like fish species classification.

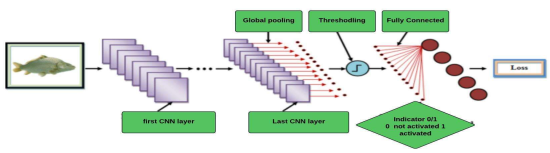


Figure 5. Representation of CNN

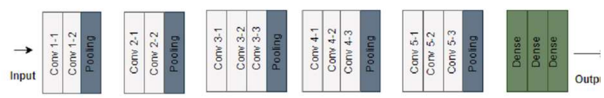


Figure 6. VGG16 model architecture

C. VGG16 (Visual Geometry Group 16)

The VGG-16 model is a convolutional neural network (CNN) with 16 layers, including 13 convolutional layers and 3 fully connected layers. Known for its simplicity and efficiency, it performs well in tasks like image classification and object recognition. The architecture consists of stacked convolutional layers followed by max-pooling layers shown in Figure 6, enabling the model to learn complex, hierarchical visual data representations. Despite being simpler than modern models, VGG-16 remains popular for deep learning due to its versatility and accuracy in extracting both low-level and high-level features from images.

D. ResNet-50

ResNet50 is a highly acclaimed deep convolutional neural network architecture known for its outstanding performance in image classification tasks. The term "ResNet50" indicates that it has 50 layers, demonstrating a significant level of depth in the architecture of the neural network. This Architecture is based on the well-known Residual Network (ResNet) paradigm. ResNet50 is notable for its use of residual connections, which are a crucial innovation. These connections facilitate the network in acquiring residual functions, which essentially enhance the process of mapping from input to output. ResNet50 effectively addresses the issue of vanishing gradients by integrating residual connections, which allows for the training of deeper networks. The ResNet50 architecture consists of four essential components: the identity block, convolutional block, fully linked layers, and convolutional layers. The identity block and convolutional block are essential components in the manipulation and conversion of features obtained by the convolutional layers from the input image. Ultimately, the completely connected layers are accountable for the ultimate classification. In ResNet50's convolutional layers, batch normalization and ReLU activation are applied after several convolutional operations. These layers play a crucial role in extracting fundamental characteristics, such as edges, textures, and forms, from the input image. In addition, Figure 7 demonstrates the utilization of max-pooling layers to decrease the spatial dimensions of feature maps while preserving important features. This strategic design improves the network's capacity to identify complex patterns in images.

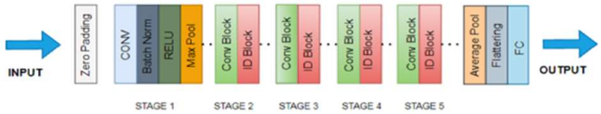


Figure 7. RestNet50 model architecture

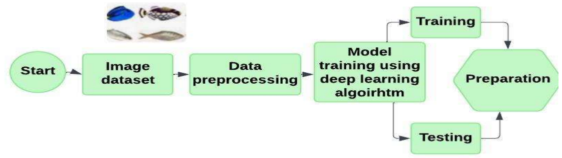


Figure 8. Flow diagram of work

Comparison of CNN with Other Models: In this fish species classification study deep learning framework is utilized, when analyzing the results one can show where and how CNN performed better or has some advantages compared to other classification methods. Convolutional Neural Networks (CNNs) have emerged as the leading approach for fish species classification due to their ability to automatically learn hierarchical features from raw image data. Unlike traditional machine learning models such as Support Vector Machines (SVMs) or decision trees, CNNs excel at capturing spatial patterns and relationships within images, making them particularly effective for tasks requiring image recognition and classification. Transfer learning further enhances CNNs' utility by leveraging pre-trained models like ResNet or Inception, which have been trained on large datasets like ImageNet, thereby accelerating training and improving accuracy. While SVMs and decision trees offer simplicity and interpretability, CNNs' superior performance on image-based tasks, especially with large datasets, underscores their dominance in fish species classification tasks where image detail and feature extraction are critical. The comparison is done analytically, on the one hand, in terms of the model's performance, and, on the other hand, comparatively, between the merits and demerits of each model in the context of training time, ease of implementation and sensitivity to variations in the used dataset. The conclusion repeats the title emphasizing the conditions that make CNNs better, or other models and models' conditions were better, describing the obstacles faced and possible enhancements in the future. This multifaceted perspective will confirm or refute the appropriateness of CNNs in range comparisons with other models, notably for fish species recognition.

Feature Extraction: This subsection explains the process of feature extraction for fish species identification from fish images. Important representations and patterns from the photos are extracted as part of the feature extraction process. After the feature extraction procedure, the feature vectors extracted from the raw data (a fish image) are delivered to the CNN, which has been trained with the training dataset. After the retrieved features are sent to the predictive model, they are compared with the test data. The species of that particular fish in the picture is then predicted by the algorithm

Platform Utilized: This study utilized Google colab and orange tool. The platform includes a powerful 16 GB 12th Gen Intel(R) Core (TM) i7 processor running at 1.70 GHz with a 64-bit operating system. The primary tool for running the source code is Google Colab, a cloud-based platform from Google Research that allows online Python programming. Colab is particularly advantageous for data analysis, machine learning, and model training due to its access to shared GPU hardware without requiring local installation. Matplotlib is used for visualizing model performance graphs, while the Orange data mining and visualization tool complements these capabilities.

System Implementation Workflow: Figure 8 outlines a structured workflow for developing a Convolutional Neural Network (CNN)-based model for fish species classification. The process begins with the acquisition of a fish species image dataset, which is essential for training and testing the model. This dataset undergoes data preprocessing to prepare it for effective model training. Preprocessing steps include resizing images, normalizing pixel values, augmenting images through techniques like rotations and flips, and splitting the data into training and testing sets. Once the data is preprocessed, it is used to train the CNN. The training phase involves the CNN learning to identify and extract relevant features from the fish images through a series of convolutional layers, pooling layers, and fully connected layers, refining its ability to classify different species. After training, the model's performance is evaluated using the test set to assess its ability to accurately classify fish images it has not encountered before, measuring metrics such as accuracy, precision, recall, and F1 score. The final step involves using the trained model for classification, where it predicts the species of new fish images based on the learned features.

Compare Matlab with Other Tools: When considering MATLAB for fish species classification compared to other tools, several factors influence its suitability and effectiveness. MATLAB's strength lies in its comprehensive tool sets like the Statistics and Machine Learning Toolbox and Image Processing Toolbox, which offer a wide range of functions tailored for data preprocessing, feature extraction, and model training. Its integrated development environment (IDE) and rich visualization capabilities facilitate rapid prototyping and insightful data exploration, crucial for understanding complex datasets inherent in image-based classification tasks. However, MATLAB's proprietary nature and cost can be limiting factors, especially for researchers and practitioners seeking open-source alternatives. In contrast, tools like Python with Tensor Flow or PyTorch leverage large, active communities and extensive libraries optimized for deep learning, providing flexibility, performance, and scalability for handling large datasets and complex model architectures. Additionally, traditional machine learning tools such as Weka or Orange offer user-friendly interfaces and broad algorithm support, making them suitable for comparative analyses and exploratory studies in fish species classification.

V. RESULT AND ANALYSIS

This study investigates the use of deep learning techniques to classify fish species by leveraging the Orange data mining tool and Google Colab. The primary architecture used is a Convolutional Neural Network (CNN), detailed in Figure 9, with its performance results shown in the table. Additionally, the study compares CNN's performance with ResNet-50 and VGG16 architectures, as validated through training and testing, with results summarized in Table 6a. The system is designed to distinguish and classify the characteristics of fish species from uploaded images, identifying fish species. The CNN model, trained on 106 species, achieved an overall accuracy of 96%, significantly outperforming the VGG16 and ResNet-50 models, which achieved 82% and 84% accuracy, respectively. This demonstrates the effectiveness of the CNN model in accurately classifying fish species with 96% accuracy.

Table 6a. Results using CNN, VGG16, and Resnet50

Test on Dataset	Algorithm	Result
106 species	CNN	0.96
106 species	VGG16	0.82
106 species	Resnet50	0.84

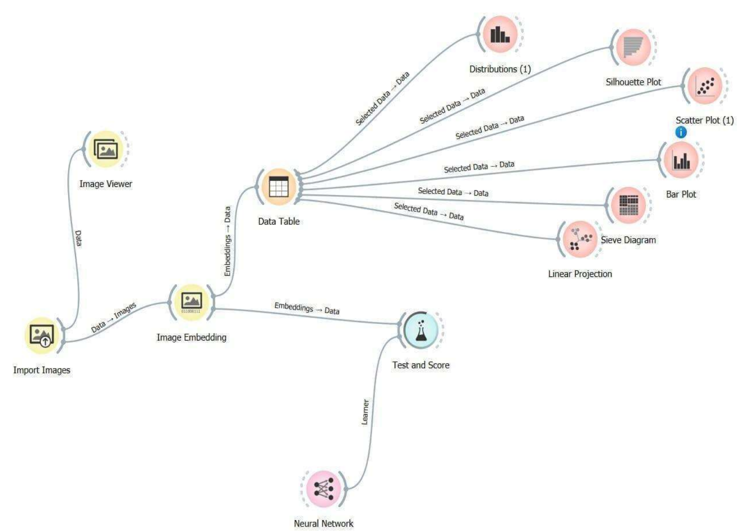
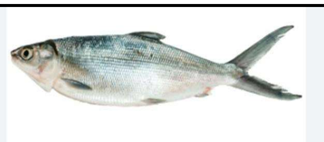


Figure 9. Visualization of Orange Framework

The framework for fish species classification as shown in Figure 10, as depicted in the provided workflow, involves several key steps using the Orange data mining tool. First, images of fish are imported into the system using the "Import Images" widget. These images are then viewed through the "Image Viewer" for preliminary inspection. The images proceed to the "Image Embedding" widget, where they are converted into a numerical representation suitable for machine learning algorithms. Next, the embedded data is fed into a "Data Table" for organization and initial analysis. Various visualizations can be generated from this data, including distributions, silhouette plots, scatter plots, bar plots, and sieve diagrams, allowing for exploratory data analysis and insights into the dataset's structure and characteristics. The core of the classification process involves training a neural network. The embedding is passed to the "Neural Network" widget, which learns to classify the fish species based on the provided images. The performance of this neural network model is evaluated using the "Test and Score" widget, which provides metrics on the model's accuracy and effectiveness. This comprehensive framework leverages image processing, data visualization, and machine learning to classify fish species, demonstrating an efficient workflow from image import to model evaluation. Table 7 evaluates the performance of a deep learning model designed for fish species classification, specifically focusing on how well it predicts species based on images sent from an end-user device. The table includes columns for the serial number, the input image, the model's actual output, the expected result, and the status of the prediction (pass or fail). In the first test case, the input image is of a fish that the model predicted as "catfish." However, the expected result was "bangus," leading to a status of "fail". Table 7 illustrates the effectiveness of the deep learning model in correctly classifying fish species, highlighting instances of both accurate and inaccurate predictions.

Table 7. Prediction Outcomes for Pictures Sent from An End User Gadget.

S.No.	Input	Actual output	Expected result	Status
1		catfish	bangus	Fail
2		Bighead carp	Bighead carp	pass

V1. KEY PERFORMANCE INDICATORS

This section defines the metrics (or KPIs, Key Performance Indicators) used to be able to evaluate the results of the algorithms.

A. Accuracy

The numeric value indicating the performance of the predictive model is shown in Eq. (1).

$$Accuracy = \frac{TP+TN}{TP+TN+FN+F}, \quad (1)$$

Where:

TP is a true positive. The outcome indicating that the algorithm accurately anticipates the positive category.

FP is a false positive. False positive: a result in which the model inaccurately forecasts the positive class.

True Negative (TN) refers to a result that correctly identifies a negative outcome in a binary classification problem. The outcome in which the model accurately forecasts the negative category.

FN is a false negative. False negative outcome, where the model inaccurately predicts the negative class.

B. Specificity

The specificity of a model, also known as the true negative rate, quantifies the percentage of negative cases that are correctly classified. The total number of negatives is the aggregate of the correctly classified negatives and the wrongly classified negatives. The calculation is performed according to Eq. (2).

$$Specificity = \frac{TN}{TN + FP'} \qquad (2)$$

C. Precision

Precision is the ratio of true positive cases to the total number of examples classified as positive. That is when a model makes predictions that are greater than zero. The calculation is performed according to Eq. (3).

$$Precision = \frac{TP}{TP + FN'} \qquad (3)$$

D. Recall

Recall is defined as the number of correctly classified positives over the total number of positives. This formula is the same as that for sensitivity. It is calculated as in Eq. (4)

$$Recall = \frac{TP}{TP+FP'} \qquad (4)$$

V11. CONCLUSION AND FUTURE WORK

The Fish Species Classification culminates with a significant breakthrough in using advanced machine learning and deep learning techniques to accurately identify and categorize fish species and its freshness as well. The deployed models, which include Convolutional Neural Networks (CNN) and its two architectures RESNet 50 and VGG 16 have proven effective in handling the complexity of species recognition in aquatic environments. The research findings not only advance the area of computer vision, but they also have practical implications for fisheries management, environmental monitoring, and biodiversity conservation. The research success demonstrates the power of combining cutting-edge technology to improve understanding of fish species variety and behavior, paving the door for sustainable resource management and ecosystem preservation. The suggested method is intended to differentiate and classify the properties of fish species from uploaded photos, hence identifying fish species. The CNN model, trained on 106 species, obtained an overall accuracy of 96%, beating the VGG16 and ResNet-50 models, which had accuracies of 82% and 84%, respectively. This displays the efficiency of the CNN model in correctly classifying fish species with 96% accuracy. Monitoring evolving technology and fish-watching trends will inform future updates and additions to the fish identification program. The mobile app will soon be updated with a sound identification module. Future efforts will center on developing a dataset of sound sets. This sound dataset will be integrated into the Fish ID application during the model training phase. The dataset extension is intended to improve the fish identification application by employing larger datasets for more precise and accurate findings. Figure 7 illustrates the main screen of a smartphone application designed to recognize fish species and measure freshness. The app is branded with the "Fish Species Detector" logo at the top of the screen, which sets the tone for the app's functionality.

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