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Environmental Management through Machine Learning-based Fish Species Classification for Sustainable Fisheries

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ABSTRACT

Fish species classification is crucial for understanding and preserving marine biodiversity. Advanced technologies such as computer vision and machine learning facilitate the identification and classification of different fish species based on their unique physical characteristics. Automatic fish classification systems are essential for biodiversity assessment, fisheries management, and environmental monitoring. This process involves collecting the image data of fish, extracting relevant features, and training machine learning models. Preprocessing the image data using Gaussian and median filters removes noise and enhances image quality. Mathematical morphological operations are employed for segmentation. For feature extraction, Gray Level Co-occurrence Matrix (GLCM) and geometrical features are used. The GLCM extracts texture features, while geometrical features describe the shape and structure of the fish. Classifiers such as Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) are then used to train the data, comparing it with the extracted features to achieve high accuracy in classification. This accurate classification is critical, especially considering the impact of environmental factors and fish species reduction on the balance of marine ecosystems. Changes in fish population can disrupt the ecological balance, highlighting the importance of effective monitoring and management systems to protect oceanic and sea environments.

Keywords: Convolutional Neural Networks; Support vector machine; Fisheries management; GLCM; Geometrical features.

1. INTRODUCTION

Understanding and preserving marine biodiversity is crucial for maintaining the balance of ocean and sea ecosystems. Advanced technologies such as computer vision and machine learning have become instrumental in identifying and classifying fish species based on their unique physical characteristics. Automatic fish classification systems are essential tools for biodiversity assessment, fisheries management, and environmental monitoring. These systems involve collecting the fish image data, extracting relevant features, and training machine learning models to achieve high classification accuracy. Effective classification is particularly important as environmental factors and reductions in fish species significantly impact the ecological balance, underscoring the need for precise monitoring and management strategies.

Fish species classification using machine learning has emerged as a transformative and innovative approach in the field of fisheries management, addressing key challenges in sustainable resource use and conservation. Fisheries around the world are under pressure from overfishing, habitat destruction, and climate change, and require advanced tools for efficient and accurate identification of species (Jalal *et al.* 2020). Machine learning's ability to analyze large datasets and identify complex patterns makes it a promising solution for improving the accuracy and effectiveness of fisheries management. Traditional methods of identifying fish species often require labour-intensive manual processes by fisheries experts. This approach is time-consuming, error-prone, and can impede the timely implementation of conservation measures. Machine learning, on the other hand, uses computational algorithms to automate and optimize the classification process, providing a faster and more reliable way to identify fish species. The methodology behind fish species classification using machine learning is based on the analysis of various features extracted from fish specimens. These traits range from traits such as morphological traits, scale patterns, and genetic markers. By compiling comprehensive datasets across a diversity of fish species, machine learning models can be trained to recognize subtle patterns and relationships within these traits, ultimately leading to a state, where accurate classification will be possible. The importance of this technological advance lies not only in the speed and accuracy of species identification, but also in its potential to revolutionize many aspects of fisheries management. Real-time monitoring, a cornerstone of effective fisheries management, is becoming possible through continuous analysis of data streams using machine learning. Whether using underwater sensors, cameras, or genetic samples, this technology allows authorities to dynamically assess fish population, species composition, and environmental conditions to make informed and timely decisions.

The benefits of machine learning extend beyond species identification and play a key role in population estimation, a key component for measuring the health and sustainability of fish stocks. Machine learning models contribute to more accurate population estimates by analyzing data on fish size, age, and abundance. This information provides the basis for setting appropriate catch limits, enforcing size regulations, and developing conservation strategies to prevent overfishing and promote the long-term health of aquatic ecosystems. Importantly, integrating machine learning into fisheries management can address the pervasive problem of illegal, unreported, and unregulated fishing. Machine learning models can detect suspicious behaviour that indicates illegal activity by continuously monitoring fishing activity and reviewing data for fraudulent activity. Fish species classification using machine learning represents a paradigm shift in the approach of fisheries management, and by automating and improving the identification process, machine learning can contribute to more effective and responsive management strategies. From real-time monitoring to population estimation to conservation efforts, this technology integration promises to lead to the responsible and sustainable use of aquatic resources. Thus, it is inevitable in the field of environmental studies (Salman *et al.* 2016).

2. LITERATURE SURVEY

Kandimalla *et al.* (2022) have proposed deep learning techniques for the automated detection, classification and counting of fish. In this paper, methodologies like You Only Look Once-version 3 (YOLOv3) and Mask R-CNN are used. Using a combination of sensors such as acoustic devices, visual sonar, active sonar, and optical cameras, and real-time detection, classification and counting of fish is possible. This state-of-the-art deep learning framework, combining convolutional neural networks (CNN) and Kalman filters, successfully identified and classified multiple fish species.

Iqbal *et al*. (2021) proposed an automatic fish species identification system based on a simplified AlexNet model with four convolutional layers and two fully connected layers. This model outperforms the original His AlexNet and His VGGNet, with fewer training images and reduced computational complexity due to the inclusion of a dropout layer, resulting in a 90.48% accuracy on the fish dataset. The system helps marine biologists understand fish species and their habitats.

Hridayami *et al.* (2019) have proposed a deep CNN, specifically ImageNet's pre-trained VGG16 model, for fish detection in aquaculture and marine biology. The dataset contains 50 species of fish, each represented by 15 images. The training included four types of His datasets: RGB images, Canny filter images, blended images, and blended images combined with RGB. The highest true acceptance rate (TAR) of 96.4% was achieved by the model trained on a blend of RGB blended images, followed by his RGB images at 92.4%. Skillful image filtering and image blending resulted in low TAR values of 80.4% and 75.6%, respectively.

Allken *et al.* (2019) used deep learning neural networks to automate species classification in deep-field trawl camera images. Acoustic trawl surveys are important for marine resource management and environmental monitoring, but identifying species from acoustic signals is difficult. Troll camera systems provide high-resolution ground data. To handle the limited training data, they used a new approach with realistic image simulation. The model achieved an impressive 94% accuracy in classifying white-breasted herring, Atlantic herring, and Atlantic mackerel, demonstrating the efficiency and feasibility of automatic species classification and the use of synthetic data to overcome the limitations of training data.

Maheswaran *et al.* (2023), Maheswaran *et al.* (2022a) and Sung *et al.* (2017) described real-time fish detection using a CNN and a YOLO algorithm. Using real fish video images, the method achieved a high classification accuracy of 93%, 0.634 over-union intersection with the ground truth bounding box, and fast fish detection of 16.7 frames per second. In particular, it outperforms fish finders that use sliding window algorithms and classifiers trained on histograms of directional gradient features and SVMs.

Rathi *et al.* (2017) proposed an automatic classification of fish species, which is an important part of ichthyology and marine biology. Accurate fish classification is essential to understand fish behavior and conservation efforts. This study presented an innovative approach to meet the needs of counting species and identifying endangered species in various water bodies. By leveraging CNN, deep learning, and image processing, the proposed method achieved an impressive accuracy of 96.29%. This method represents a significant advance in fish species identification, surpassing previous techniques and providing a valuable tool for agencies involved in monitoring aquatic ecosystems and protecting endangered species in large and small bodies of water.

Salman *et al.* (2016) proposed machine learning approach that uses a CNN model with a hierarchical feature combination setup. Underwater video and digital cameras are becoming increasingly popular in marine research for quantifying marine life, especially fish. Manual analysis of these images is time-consuming and costly, requiring automated fish classification, counting, and measurement. Underwater scenes are very different, with changing light, fish movement, dynamic backgrounds, and visual similarities between different species. It learns species-specific visual features that are distinct and resilient to environmental and species fluctuations. The method has achieved high accurate classification rates of over 90% on benchmark fish datasets (LifeCLEF14 and LifeCLEF15), making it a valuable tool for marine scientists and managers in assessing marine fauna.

Prasetyo *et al.* (2022) proposed a fish classification system using CNN that eliminates the need for manual feature extraction and analysis. A new approach called multilevel residual (MLR) was used, along with Depthwise Separable Convolution to combine the low-level features of the first block with the high-level features of the last block. Furthermore, MLR-VGGNet, a CNN architecture based on VGGNet, was extended with asymmetric convolution, MLR, batch normalization, and residual function. Experimental results show that MLR-VGGNet achieves an excellent accuracy of 99.69%, outperforming the original VGGNet by up to 10.33% and other CNN models by up to 5.24% on Fish-gres and Fish4-Knowledge datasets. This innovation significantly advances the field of fish species classification.

Park *et al.* (2019) proposed a fish species classification algorithm as a preliminary step to eliminate invasive fish species. Two datasets were used. Dataset 1 was aimed at improving image diversity, while Dataset 2 was aimed at more natural environmental conditions. The classification accuracy of four CNNs exceeded 99.97% on dataset 1 and 99.5% on dataset 2. In particular, the CNN trained on dataset 2 showed superior performance in natural environments. Among the CNNs, AlexNet was found to be the most suitable choice due to its high performance, short execution time and training time, making it ideal for the fish species exclusion system.

Maheswaran *et al.* (2022) and Mathur *et al.* (2020) used cross-convolutional layer pooling on a pre-trained CNN. Automatic classification of fish species is of great importance to ecologists and marine biologists. Traditional methods are labor-intensive and costly, requiring the development of automated systems to detect, track, and classify aquatic species in underwater images. Underwater situations with low-resolution images and cluttered backgrounds challenge traditional computer vision techniques. Artificial neural networks (ANNs) and deep neural networks show promise, but training is hampered by limited fish image datasets. The method achieved a validation accuracy of 98.03% on a dataset of 27,370 fish images, providing an efficient alternative to manual detection by marine experts and monitoring fish biodiversity in natural habitats.

Hasija *et al.* (2017) designed an automatic classification of fish species for marine biologists to study underwater ecosystems and detect endangered species. Traditional methods are often laborious, computationally intensive, and require automated approaches. Classifying underwater images is difficult due to calibration issues, resulting in distortion, noise, occlusion, and variable image quality. They proposed an innovative method based on improved image set matching using graph embedding discriminant analysis. Unlike single-image methods, this approach used explicit image set matching, which improved computational stability. Compared to previous classification techniques, identification accuracy was significantly improved, providing a valuable tool for marine research and conservation efforts.

Jalal *et al.* (2020) proposed an accurate monitoring of fish abundance, distribution, and movements in migratory fisheries for ecological research and environmental management. Manual monitoring is time and resource intensive. This study recorded images of nine target fish species, extracted and refined their contours using a novel shape analysis algorithm. Fish species classification was done by comparing contour segments to a database to achieve accurate pattern matching. Automated fish classification systems simplify data collection and improve the accuracy and efficiency of fisheries monitoring.

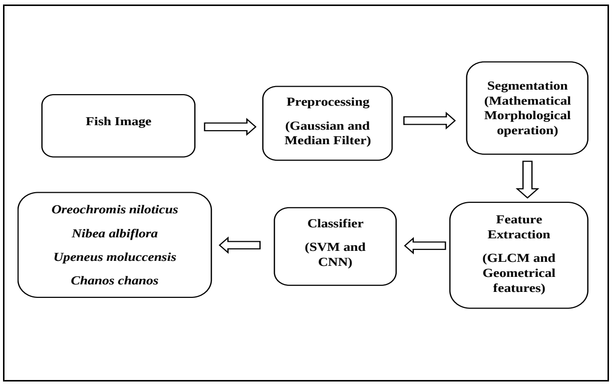


Fig. 1: Proposed block diagram

3. PROPOSED METHOD

The proposed methodology is shown in Fig. 1. Preprocessing is done with the image data of fish species by using Gaussian and median filters. Mathematical morphological operations are used for segmentation. Gray Level Co-occurrence matrix (GLCM) is used to extract texture features of fish and geometrical features describe the shape and structure of the fish. For classifier, SVM and CNN are used (Prasetyo *et al.* 2022).

3.1 Dataset Collection

The classification of fish species is done with the help of the machine learning techniques. Four different species of fish are classified. Datasets of these species have been taken and trained using CNN. Table 1 shows the datasets count of different fish species. This proposed method relies on a well-compiled image dataset containing images of fish species such as Oreochromis niloticus, Nibea albiflora, Upeneus moluccensis, and Chanos chanos. It is planned in a way to capture species size, shape, and appearance in different environmental conditions.

Table 1. Collection of datasets

S. No.	Different Fish Species	Count
1.	*Oreochromis niloticus*	560
2.	*Nibea albiflora*	250
3.	*Upeneus moluccensis*	150
4.	*Chanos chanos*	500

3.2. Data Preprocessing

When classifying fish species, preprocessing includes data cleaning, resizing, normalization, and data augmentation. These steps optimize the dataset for machine learning or deep learning model to improve accuracy and generality in identifying fish species. Gaussian filters act in smooth way and reduce image noise by applying a weighted average to pixel values. Median filter removes noise by replacing a pixel value with the median value of its local neighbourhood. These filters improve image quality, reduce artifacts, and aid in accurate species identification.

Gaussian Filtering: The process reduces and smoothens the noise in the images, improving the overall quality without an escape of important details. Equation 1 shows the Gaussian filtering kernel for 2D image

$$G(i,j) = \frac{1}{2\pi\sigma^2} e^{-\frac{i^2+j^2}{2\sigma^2}} \quad \ldots (1)$$

i, j -Pixel Co-ordinates
σ-Standard Deviation

Median Filtering: This method is used in noise-reduction; median filtering is most efficient against the removal of salt-and-pepper noise, which is a common disturbance phenomenon in underwater photography.

3×3 window size is selected to extract the pixel value and the centre pixel value is replaced by average of the values

$$I_{filtered}(x,y) = \text{median}\{I(x+m,y+n)\ |m,n\in[-k,k]\} \quad \ldots (2)$$

I(x+m, y+n) : Intensity values in the (2k+1)×(2k+1)\ neighborhood around (x,y)
k : kernel size

Equation 2 is the mathematical representation of median filter. Gaussian Filter is used for initial noise reduction and contour detection is applied to the median filter for detailed texture analysis and feature extraction.

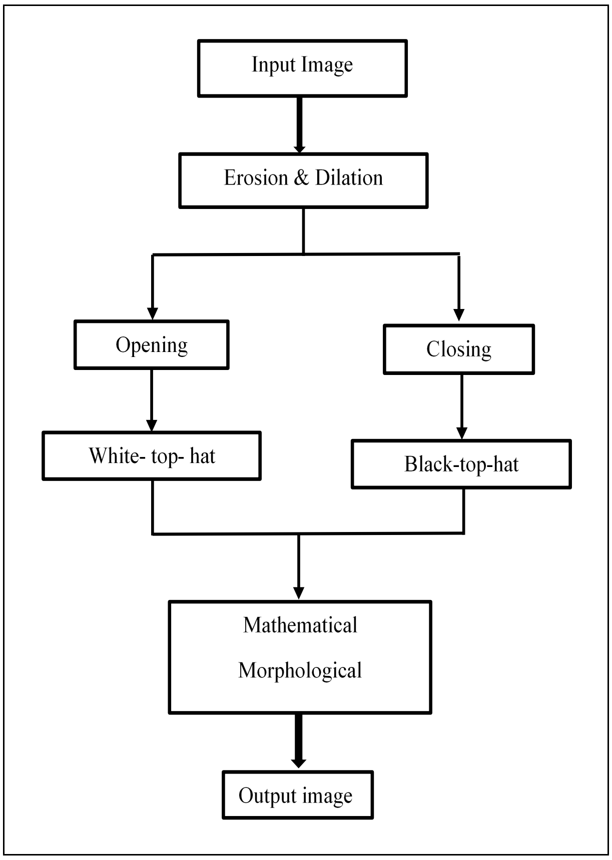


Fig. 2: Mathematical morphological operation

3.3 Segmentation

Segmentation in fish species classification involves separating individual fish in an image or video. This allows for accurate depiction of fish shapes and facilitates more accurate feature extraction and classification based on specific characteristics of each fish, such as: size, shape, and colour. Mathematical morphological operations play an important role in image segmentation for classifying fish species. Image segmentation involves dividing an image into different regions that correspond to different objects or features within the image. Mathematical morphological operations include dilation, erosion, opening and closing.

Erosion is used to erode or reduce the boundaries of areas within an image. When classifying fish species, it can be used to reduce the size of objects, remove small noises and artifacts, and separate closely related fish. By applying these morphological operations, their shape and size can be improved, and unnecessary elements can be removed from the image. This process simplifies the task of feature extraction and enables the measurement of distinctive features such as size, shape, and colour that are important for fish species classification. The block diagram for the mathematical morphological operation is shown in the Fig. 2.

3.4 Feature Extraction

Feature extraction in fish species classification involves capturing key features or patterns from images or data to represent fish species. In this context, features may include colour histograms, texture descriptors, shape measurements, etc. The GLCM is a powerful texture analysis tool used in classifying fish species based on image data. The GLCM captures the spatial relationships between pixel values in an image and provides valuable textural information that can be used to distinguish between different species based on their unique visual characteristics. Fish species are classified according to their geometrical characteristics, which include a variety of morphological features. These features are essential for ichthyological (fish biologist) classification and categorization. Some of the most important geometrical characteristics include the body shape, the placement and structure of fins, the scale patterns, the shape of the head and mouth, and the size and shape of the gills.

GLCM generates features like contrast, correlation, energy, and homogeneity, which provide a complete texture profile for an image.

$$\text{Contrast} = \sum_{x=0}^{N-1}\sum_{y=0}^{N-1}(x-y)^2.P(x,y) \quad \ldots (3)$$

$$\text{Correlation} = \sum_{x=0}^{N-1}\sum_{y=0}^{N-1}\frac{(x-\mu_x)(y-\mu_y)P(x,y)}{\sigma_x\,\sigma_y} \quad \ldots (4)$$

$$\text{Energy} = \sum_{x=0}^{N-1}\sum_{y=0}^{N-1}P(x,y)^2 \quad \ldots (5)$$

$$\text{Homogeneity} = \sum_{x=0}^{N-1}\sum_{y=0}^{N-1}\frac{P(x,y)}{1+|x-y|} \quad \ldots (6)$$

Equations 3, 4, 5 and 6 are used to calculate the scale pattern, repetitive patterns or spots, texture regularity and spices with uniform body shapes.

Geometrical features concentrate on dimension, structure and shape. Width and length measurement by measures the minor and major axes of fish spices it gives the basic outline size. Equation 7 is used to calculate the body portion of the fish.

$$\text{Aspect Ratio} = \frac{\text{Length}}{\text{Width}} \quad \ldots (7)$$

Circularity is another feature that represents the complexity and boundary of the fish species. Equation 8 shows the circularity calculation of species.

$$\text{Circularity} = \frac{4\pi X\text{Area}}{\text{Perimeter}^2} \quad \ldots (8)$$

The final geometrical feature is contour irregularity, which is used to identify the tail, body and fins of fishes. Combination of features from GLCM (Texture based) and Geometrical (Shape based) gives the full characteristics and specification of fish species leading to a perfect classification method.

3.5 Classifier

When classifying fish species, a classifier that determines the fish species based on extracted features and image data, which is an important component. A variety of classifiers, including traditional machine learning algorithms such as SVMs, random forests, and k-nearest neighbours (k-NNs), as well as deep learning models such as CNNs are used. The SVM is a powerful machine learning algorithm used to classify fish species based on visual features. The SVM features binary and multi-class classification tasks, making it suitable for differentiating different fish species. The SVM works by finding the optimal hyperplane that maximizes the distance between different fish species in a high-dimensional feature space. This allows to effectively separate species based on different visual characteristics such as shape, colour, and texture. The architecture of the SVM is shown in the Fig. 3.

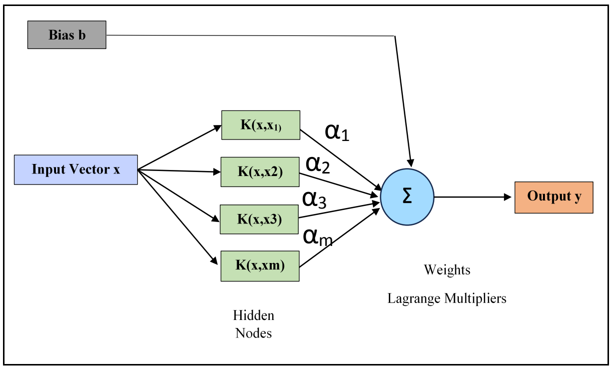


Fig. 3: Support vector machine

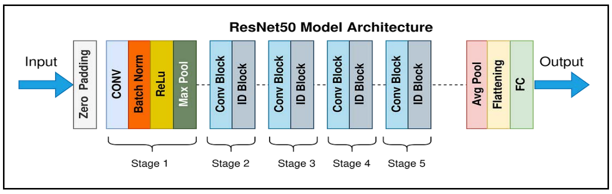


Fig. 4: ResNet50 model architecture

The CNNs are very effective choice for classifying fish species. The CNNs are well-suited to processing image data, making them robust and accurate classifiers in this situation. With its 50-layer design, ResNet50, a deep CNN, performs exceptionally well in fish species classification. It has been trained on large datasets and can recognize fine details in fish photos, allowing for reliable species categorization. Because of the deep residual learning framework of the model, vanishing gradient problems are lessened, improving performance and permitting reliable identification of various fish species in aquatic settings. Fig. 4. represents the architecture of ResNet50.

Convolutional Neural Network: It is a well-known method for learning complex patterns from images. This structure is deep enough to recognize and learn hierarchically from simple edges to very complex textures and shapes. The CNN model is trained for robustness along with high accuracy, even in challenging conditions. Fig. 5 shows the CNN architecture.

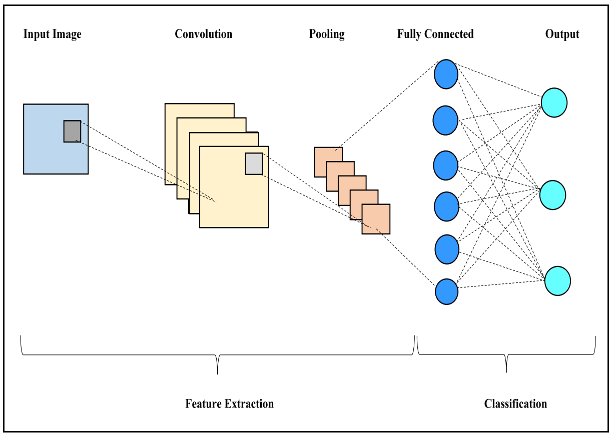


Fig. 5: CNN structure

The proposed method is useful in biodiversity monitoring, fisheries management and conservation activities.

4. EXPERIMENTAL STUDY AND ANALYSIS

To assure the usefulness and dependability of a machine learning model, an experimental investigation and analysis are essential. It is used to confirm the model's effectiveness, spot any flaws, and unearth knowledge that can help with improvements. We can determine the model's generalizability to new data, comprehend its constraints, and fine-tune its parameters and features through rigorous evaluation. Such analysis is essential for resolving ethical issues, bias reduction, and ensuring the model's practical value. It also improves the model's performance and accuracy. Fig. 6 shows the flow chart of analysis of fish species. The fish data set given to the preprocessing which includes noise removal, segmentation, resizing and normalization. The texture features and geometrical features are extracted. Both the features are given to the CNN model to classify the type of fish.

4.1 Performance Metrics

In the fish classification model, sensitivity calculates the ratio of definite fish species that the typical correctly recognizes as belonging to a specific category. Sensitivity imitates the model's capacity to recognize elusive morphological and texture features exact to fish species. An advanced sensitivity permits the system to identify complicated outlines, such as scales or body shapes, enlightening its performance in distinctive between similar species.

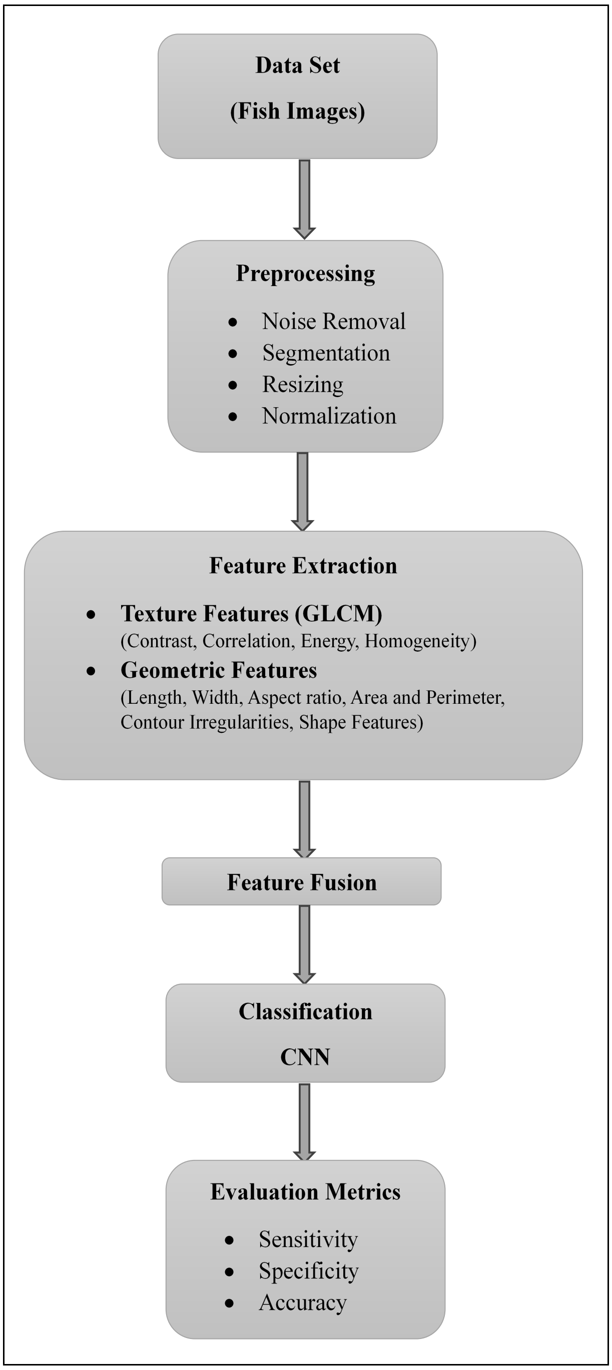


Fig. 6: Flow chart

Specificity evaluates the ratio of dissimilar fish species that the technology correctly predicts as not belonging to a given category. Specificity evaluates the model's capacity to reduce false classifications, confirming precise refusal of unrelated features or species. A higher specificity improves precision.

Accuracy measures how well a model correctly classifies or identifies objects or patterns in images.

5. RESULTS AND DISCUSSION

The dataset count of fish species was 1460. The species types were Oreochromis niloticus, Chanos chanos, Upeneus moluccensis, Nibea albiflora. Results obtained from the segmentation and image of the identified species are attached below. The accuracy of the CNN and Random Forest classifier are plotted according to (Prasetyo *et al.* 2022). There are 25 true positive cases, 2 false negatives, 2 false positives and 5 true negatives. These values provide an overview of the model's performance, highlighting its ability to accurately classify the fish species. Sensitivity and specificity values are 92.59% and 71.42%. The accuracy level of the proposed method is 88%. Table 2 shows overall values of the parameters obtained.

Input image with noise added (a)

Final denoised image (b)

Fig. 7: (a) Noisy image, (b) Denoised image

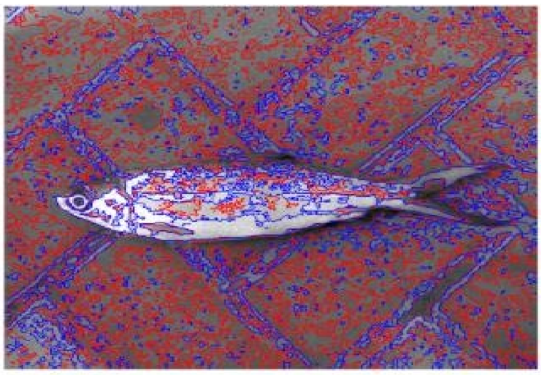
The Fig. 7. represents the denoised image of the fish using the Gaussian filter and Median filter. These filters are applied before feeding them into the CNN model. Gaussian filtering is used for smoothing the images. It helps reduce noise and detail in the image, making it more robust to variations in lighting and minor imperfections. Median filtering is effective in removing impulse noise or salt-and-pepper noise from images. It replaces each pixel value with the median value in its neighbourhood, making it robust to outliers.

Table 2. Parameters

S. No.	Parameters	Values
1	Overall Sensitivity	92.59%
2	Overall Specificity	71.42%
3	Overall Accuracy	88%

Mathematical morphological based segmentation

Fig. 8: Mathematical morphological based segmentation



60 Iterations

Fig. 9: Feature extraction

The result obtained from the segmentation process by using mathematical morphological operation is shown in the Fig. 8. It separates a fish from the background and from its shadow. It involves the operations like dilation, erosion, opening and closing to enhance the features of interest and separate fish from background. Opening helps to remove small-scale noise and smoothens the contours of objects. Dilation is used to expand the brighter regions in the image, potentially connecting broken parts of fish structures. Erosion is used to shrink the regions, focusing on enhancing fish-like structures. Closing helps to fill small holes in the fish regions and close gaps in the contours. Fig. 9. shows the iterations, while applying feature extraction techniques like GLCM and geometrical features. By using GLCM: colour entropy, coarseness lesion, gray-level non uniformity, short run low gray-level emphasis and long run low gray-level emphasis values are identified. Values are identified by using the geometrical features such as, radial variance, asymmetry, compactness, colour variance, and area etc.

For classifier, SVM and CNN are used. These classifiers are used to train the data and it compares it with the feature extracted values and gives the result. The identified fish species using the SVM and CNN (ResNet50) are shown in the Fig. 10.

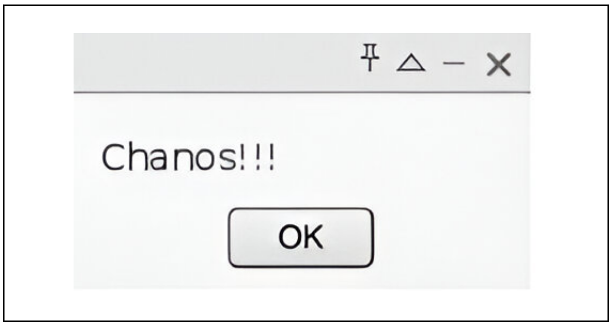


Fig. 10: Identified fish species

The Fig. 11. shows the difference between the accuracy of CNN and a Random Forest classifier.

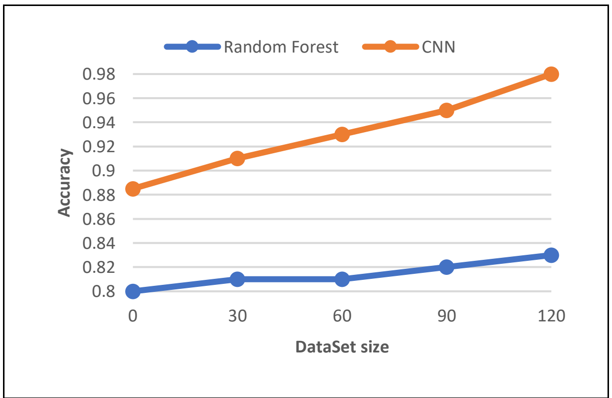


Fig. 11: Accuracy of CNN vs Random forest classifier

6. CONCLUSION

In conclusion, fish species classification is an important research field with important implications for various fields such as fisheries management, aquatic ecology, conservation, and biodiversity research. Initially, the image data of fish species are pre-processed by using Gaussian and median filters. Mathematical morphological operations are used for segmentation. For feature extractions, GLCM and geometrical features are used. For classifier, SVM and CNN are used. These classifiers are used to train the datasets and it compares it with the feature extracted values and gives the result. This study obtained an accuracy of 88%, similar to (Shammi *et al.* 2021) who got an 88.96% classification accuracy. From this, the classification of fish species with high accuracy is achieved.

The future scope for the classification of fish species is poised for significant growth with the ongoing advancements in technology. Machine learning and computer vision, coupled with big data and genetic analysis, will empower researchers to create more robust and precise fish species identification tools. Integration with underwater drones and remote sensing systems will expand the scope of data collection, making it easier to identify and monitor fish species in their natural habitats. These developments hold great potential for improving conservation efforts, promoting sustainable aquaculture and fisheries management, and aiding in ecological preservation. Moreover, such innovations may find applications in citizen science initiatives and recreational fishing, enhancing our understanding of aquatic ecosystems.

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CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

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