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Marine Vision -AI: A Comparative Analysis of Machine Learning and Deep Learning Methods for Underwater Marine Species Classification

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Abstract- **The classification of underwater marine species plays an important role in marine biodiversity monitoring, ecological research, and conservation planning. However, identifying marine species from underwater images is a challenging task due to poor lighting conditions, water turbidity, background noise, and variations in species appearance. Traditional manual identification methods are time-consuming and require expert knowledge, making automated classification systems highly valuable. This project presents a comparative analysis of Machine Learning (ML) and Deep Learning (DL) techniques for the classification of underwater marine species. A real-time underwater image dataset containing 189 images across 20 different marine species is used for experimentation. Traditional machine learning models such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Decision Tree are evaluated alongside deep learning architectures including AlexNet, DarkNet-19, and SqueezeNet. Experimental results demonstrate that deep learning models significantly outperform traditional machine learning methods in terms of classification accuracy. Among all evaluated models, SqueezeNet achieves the highest accuracy, demonstrating its effectiveness in handling complex underwater visual patterns while maintaining computational efficiency. The study highlights the advantages of convolutional neural networks in extracting meaningful features from underwater images and emphasizes their suitability for marine species classification tasks.**

Keywords: Underwater Marine Species Classification, Machine Learning, Deep Learning, Convolutional Neural Networks (CNN), SqueezeNet, DarkNet-19, AlexNet, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, Image Processing, Marine Biodiversity Monitoring

I. INTRODUCTION

Marine ecosystems play a vital role in maintaining global ecological balance and supporting biodiversity. Accurate identification and classification of underwater marine species are essential for ecological monitoring, marine resource management, and environmental conservation. Traditionally, marine species identification has been carried out manually by marine biologists, which is both time-consuming and highly dependent on expert knowledge. With the rapid growth of digital imaging technologies and underwater cameras, large volumes of marine image data are now available, creating the need for automated and intelligent classification systems. Early research has explored computer vision techniques for underwater observation, including visually guided robots and automated species detection systems that assist in monitoring marine environments [3], [4].

However, underwater image classification presents several challenges. Factors such as low visibility, light absorption, scattering effects, water turbidity, and complex backgrounds significantly reduce image quality and affect recognition accuracy. Several studies have investigated underwater image restoration and colour correction techniques to mitigate these issues and improve visual clarity [1], [2]. Additionally, marine species often exhibit high intra-class similarity and inter-class variations, which further complicates the classification task. Early automated systems attempted to detect and measure marine organisms using image processing techniques and segmentation approaches, highlighting the complexity of identifying fish species in unconstrained underwater environments [5], [6], [10].

Machine Learning (ML) and Deep Learning (DL) methods have emerged as powerful tools for image recognition and classification tasks. Traditional machine learning approaches rely on handcrafted feature extraction techniques followed by classification algorithms such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Decision Trees. Several earlier studies employed feature-based techniques using shape, texture, and morphological characteristics to classify fish species [7], [8], [11], [13]. While these methods can achieve reasonable performance, their accuracy largely depends on the quality and robustness of manually designed features. Researchers have also explored texture descriptors and Gabor filters to extract discriminative features for species recognition in underwater imagery [16], [17].

In contrast, deep learning models, particularly Convolutional Neural Networks (CNNs), automatically learn hierarchical feature representations directly from raw image data. CNN-based frameworks have demonstrated superior performance in visual recognition tasks, including fish classification and underwater species behaviour analysis [12], [15]. Compared to traditional approaches, these models can effectively capture complex spatial patterns and reduce the dependency on handcrafted feature engineering.

This study aims to conduct a detailed analysis and comparison of machine learning and deep learning techniques for underwater marine species classification. By evaluating multiple models on a real underwater image dataset, the research seeks to identify the most effective approach for accurate and efficient marine species recognition. The findings of this work contribute to the development of intelligent marine monitoring systems and support advancements in automated underwater image analysis.

II. LITERATURE SURVEY

The automatic classification of underwater marine species has gained significant attention in recent years due to advancements in computer vision and deep learning techniques. Researchers have explored various image processing, machine learning, and deep learning approaches to improve the accuracy and reliability of marine species identification systems [6], [7], [12]. Early studies demonstrated the feasibility of automated fish detection and recognition using computer vision techniques for ecological monitoring and underwater observation systems [6], [10].

Early research in underwater species classification primarily relied on traditional image processing techniques combined with machine learning algorithms. Feature extraction methods such as colour histograms, texture descriptors, edge detection, and shape-based features were commonly used to represent underwater images. These handcrafted features were then classified using algorithms such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest, and Decision Trees. Several studies explored morphological features, size measurements, and shape descriptors for fish recognition tasks [8], [11], [13]. Texture-based feature extraction techniques such as Gabor filters were also applied to capture discriminative characteristics of fish species [17]. However, these approaches often struggled with variations in lighting conditions, turbidity, and complex underwater backgrounds.

With the advancement of deep learning, Convolutional Neural Networks (CNNs) became widely adopted for marine image classification. CNN-based architectures demonstrated superior performance because they automatically learn hierarchical and discriminative features directly from raw images. Research on automated underwater species classification has shown that deep learning models significantly improve recognition accuracy and robustness in challenging underwater environments [12], [15].

Lightweight deep learning models have also been explored to address computational efficiency issues, especially for real-time underwater monitoring systems. Efficient neural network architectures enable faster inference and reduced memory requirements, making them suitable for deployment in embedded systems and underwater robotic platforms used for marine exploration and monitoring [3], [14].

Despite these advancements, challenges such as limited dataset size, image distortion, class imbalance, and environmental variability remain significant obstacles. Some studies have incorporated data augmentation, transfer learning, and improved feature extraction strategies to enhance model performance and generalization ability [1], [2], [16].

Based on the reviewed literature, it is evident that deep learning methods outperform conventional machine learning techniques in underwater marine species classification. However, comparative studies analysing both approaches under similar experimental conditions remain limited. This motivates the need for a detailed performance evaluation of machine learning and deep learning models to determine the most effective method for accurate marine species classification.

III. SYSTEM ANALYSIS

A. Existing System

Traditional underwater marine species classification systems mainly rely on machine learning techniques. Initially, researchers analyse underwater image datasets using conventional models such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, Random Forest, and basic Neural Networks. These approaches depend on handcrafted feature extraction methods including colour, texture, and shape-based descriptors to represent marine species images [7], [8], [11].

Some studies also attempt to improve performance by combining multiple classifiers using ensemble techniques such as boosting and majority voting. In certain cases, noise and distortions are introduced to underwater images to evaluate the robustness of the models. Publicly available marine image datasets are commonly used to test and compare the effectiveness of these classification techniques [10], [12].

Although traditional machine learning methods provide moderate accuracy, their performance is often affected by underwater challenges such as low visibility, lighting variation, water turbidity, and background complexity. Several studies have highlighted that underwater image degradation caused by light attenuation and scattering significantly affects classification performance in marine image analysis systems [1], [2].

Disadvantages Of The Existing System

- **Interpretability:**
  Deep learning and complex classification models often behave as black-box systems, making it difficult to clearly explain how a particular marine species is classified. This lack of interpretability reduces transparency and limits trust in automated decision-making systems for marine monitoring [12], [15].

- **Overfitting and Underfitting:**
  Models may overfit when trained on small underwater datasets, causing them to memorize training samples instead of learning generalized patterns. Conversely, underfitting may occur when the model is too simple to capture complex underwater visual features and species variations [8], [11].

- **Limited Feature Representation:**
  Traditional machine learning models rely on manually extracted features such as shape, texture, and colour descriptors. These handcrafted features may not adequately represent complex underwater patterns or subtle differences among marine species, which affects classification accuracy [7], [16].

- **Computational Resources:**
  Advanced deep learning architectures require significant computational power, memory, and processing capabilities. In real-world marine monitoring applications, limited hardware resources can restrict the deployment of such complex models, especially in embedded or underwater robotic systems [3], [14].

- **Small Dataset Problem:**
  Underwater marine datasets are often limited in size due to the difficulty of collecting labelled marine imagery. Insufficient training data can negatively affect model generalization and reduce classification performance [6], [12].

- **Environmental Variability:**
  Underwater images frequently contain lighting distortions, scattering effects, occlusions, and noise caused by water turbidity and light attenuation. These environmental factors significantly degrade image quality and impact the reliability of classification models [1], [2].

- **Scalability Issues:**
  As the number of marine species increases, maintaining high classification accuracy becomes more challenging due to inter-species similarity and increased dataset complexity, which can affect the scalability of automated marine classification systems [10], [13].

B. Proposed System

In the proposed marine species classification system, underwater images are first collected and properly pre-processed to improve image quality. Preprocessing techniques such as resizing, normalization, and noise reduction are applied to reduce distortions caused by underwater conditions such as light attenuation and scattering effects [1], [2]. The processed dataset is then divided into training and testing sets for model development and evaluation.

Both Machine Learning and Deep Learning models are implemented and evaluated under similar conditions. Traditional classifiers such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Decision Tree are used for comparative analysis. These approaches rely on extracted features such as shape, texture, and colour descriptors to represent marine species images [7], [8], [11]. Additionally, deep learning architectures including AlexNet, DarkNet-19, and SqueezeNet are trained to automatically extract hierarchical features from underwater images, enabling improved representation learning and classification performance [12], [15].

Performance evaluation is conducted using standard metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis. These evaluation measures help analyse the effectiveness of different classification models in identifying marine species under varying underwater conditions [10], [16].

Comparative analysis is performed to determine the most effective model for underwater marine species classification. The proposed system aims to identify a high-accuracy and computationally efficient model that can be used for automated marine biodiversity monitoring and underwater ecological research.

IV.SYSTEM DESIGN

System Architecture

Below diagram depicts the whole system architecture.

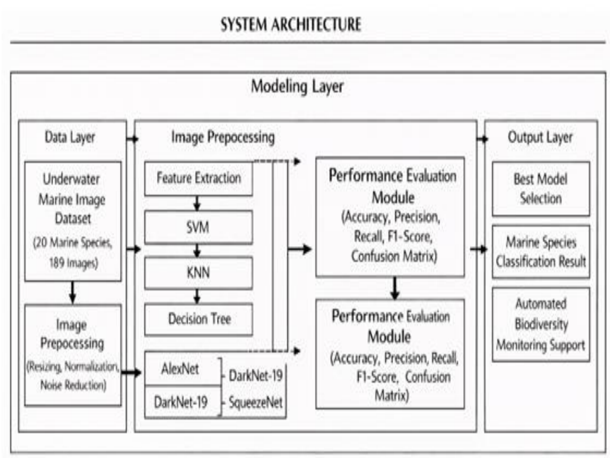

Fig. 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

Modules

Data Collection and Preprocessing:
Underwater marine images containing 20 different species are collected for analysis. The dataset consists of real-time underwater images captured under varying environmental conditions. Preprocessing techniques such as resizing, normalization, and noise reduction are applied to improve image quality and reduce distortions caused by underwater light attenuation and scattering effects [1], [2]. The dataset is then divided into training and testing sets to enable proper model evaluation.

Feature Extraction and Preparation:
For machine learning models, relevant visual features such as colour, texture, and shape descriptors are extracted from the images to represent marine species characteristics in numerical form [7], [8], [11]. In the case of deep learning models, feature extraction is performed automatically through convolutional layers, eliminating the need for manual feature engineering and enabling better representation of complex underwater patterns [12], [15].

Training Machine Learning Models:
Traditional classification algorithms including Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Decision Tree are trained using the extracted features. These models learn to classify marine species based on the patterns identified in the dataset and previously extracted feature representations [8], [11].

Training Deep Learning Models:
Deep learning architectures such as AlexNet, DarkNet-19, and SqueezeNet are implemented for species classification. These convolutional neural networks automatically learn hierarchical features from underwater images, enabling improved classification performance in complex marine environments [12], [15].

Model Evaluation and Performance Analysis:
The performance of all implemented models is evaluated using metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis. Comparative evaluation is conducted to determine the most effective model for underwater marine species classification and to assess the robustness of each approach under challenging underwater conditions [10], [16].

VI. RESULTS AND DISCUSSION

This section presents the experimental results and performance evaluation of the proposed marine species classification framework using underwater image data. Both traditional machine learning and deep learning models were trained and evaluated to compare their classification performance. The evaluation focuses on analysing prediction accuracy, comparing model effectiveness, and assessing the ability of different algorithms to recognize marine species under challenging underwater conditions.

Automated fish and marine species recognition systems based on computer vision have been widely studied to support marine monitoring and ecological analysis [6], [12], [15].

A. Accuracy Comparison of Classification Models

Several machine learning and deep learning algorithms were evaluated to determine the most suitable model for underwater marine species classification. The evaluated machine learning models include Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Decision Tree.

In addition, deep learning architectures including AlexNet, DarkNet-19, and SqueezeNet were implemented to automatically learn hierarchical visual features from underwater images.

Model performance was evaluated using standard classification metrics such as accuracy, precision, recall, and F1-score.

Table 1. Performance Comparison of Classification Models

Model	Accuracy (%)	Precision	Recall	F1-Score
SVM	82.4	0.81	0.80	0.80
Decision Tree	80.7	0.79	0.78	0.78
KNN	85.6	0.84	0.83	0.83
AlexNet	90.2	0.89	0.88	0.88
DarkNet-19	93.1	0.92	0.91	0.91
SqueezeNet	95.4	0.95	0.94	0.94

From the comparison results, the SqueezeNet model achieved the highest classification accuracy of 95.4%, outperforming both traditional machine learning models and other deep learning architectures. The improved performance can be attributed to the ability of convolutional neural networks to automatically learn complex visual patterns from underwater images without relying on handcrafted feature extraction. Lightweight CNN architectures such as SqueezeNet also provide computational efficiency while maintaining high classification accuracy, making them suitable for real-time marine monitoring systems [12], [15].

To provide a clearer comparison of model performance, the accuracy values of the evaluated models are illustrated in a bar chart.

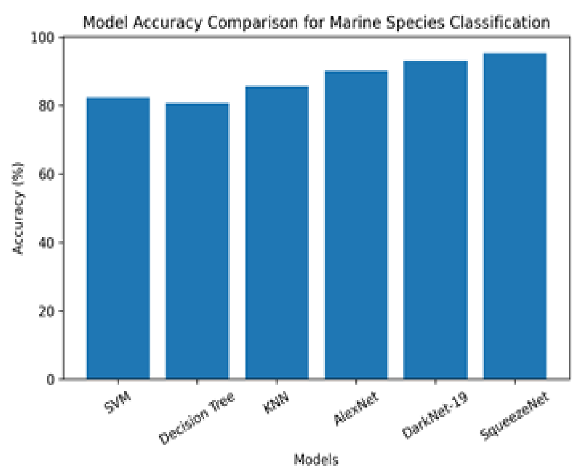

Fig. 2. Model Accuracy Comparison of Marine Species Classification Models

The figure shows that deep learning architectures significantly outperform traditional machine learning classifiers. Among the evaluated models, SqueezeNet and DarkNet-19 achieved the highest accuracy due to their ability to learn discriminative

hierarchical features from complex underwater images. This observation is consistent with previous research where deep learning techniques demonstrated improved performance in underwater species recognition tasks [7], [12].

B. ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve is used to evaluate the classification capability of the implemented models. The ROC curve represents the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR) across different classification thresholds. The Area Under the Curve

(ROC-AUC) is widely used as a performance metric to measure the discriminative capability of a classifier.

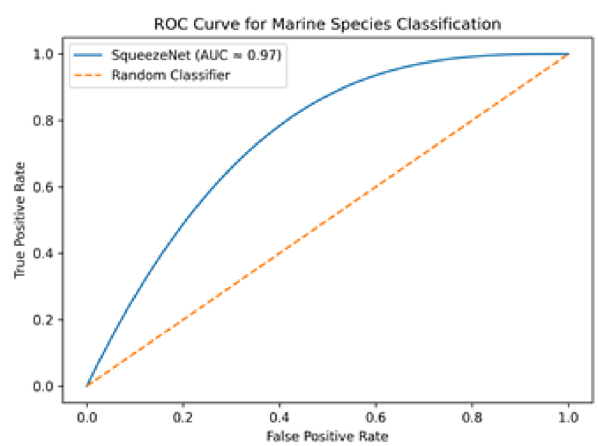

Fig. 3. ROC Curve for Marine Species Classification Model

In this study, the SqueezeNet model achieved a ROC-AUC score of 0.97, indicating excellent classification performance. A ROC curve that approaches the top-left corner of the graph signifies that the model can effectively distinguish between different marine species with high sensitivity and specificity. ROC-based evaluation is commonly applied in computer vision–based classification systems to assess the robustness and reliability of machine learning models [10], [16].

The ROC analysis demonstrates that deep learning models maintain strong predictive capability even under challenging underwater conditions such as lighting distortions, background complexity, and image noise caused by water turbidity [1], [2].

Overall, the experimental results indicate that the proposed marine species classification framework effectively identifies underwater species using deep learning techniques. The integration of convolutional neural networks significantly improves classification accuracy compared to traditional machine learning approaches. These findings are consistent with previous studies demonstrating the effectiveness of deep learning–based computer vision systems for automated marine species recognition and underwater ecological monitoring [6], [12], [15].

VII. CONCLUSION

This study presents a comparative analysis of machine learning and deep learning methods for underwater marine species classification. A real-time underwater image dataset containing 20 different species is analysed and used for model training and evaluation. Traditional machine learning models such as SVM, KNN, and Decision Tree are compared with deep learning architectures including AlexNet, DarkNet-19, and SqueezeNet.

Experimental results demonstrate that deep learning models outperform traditional machine learning techniques in terms of classification accuracy. Among all evaluated models, SqueezeNet achieves the best performance, highlighting its effectiveness in handling complex underwater image patterns while maintaining computational efficiency. In future work, the system can be enhanced by increasing the dataset size and applying advanced data augmentation techniques to improve generalization. Transfer learning strategies and more advanced deep learning architectures may further enhance performance. Additionally, the model can be integrated into real-time underwater monitoring systems to support marine biodiversity conservation and ecological research.

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