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Original Article

Automated aquatic biodiversity monitoring using deep learning on the Tigris River: Species identification and ecosystem assessment

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Abstract: Aquatic ecosystems play a crucial role in biodiversity and ecological stability but are increasingly threatened by climate change, pollution, habitat degradation, and invasive species. Traditional monitoring methods are labor-intensive, costly, and limited in spatial and temporal coverage. This study integrates deep learning techniques with biodiversity monitoring to enhance species identification, abundance estimation, and ecosystem assessment in freshwater environments. Focusing on the Tigris River, Iraq, we developed convolutional neural network (CNN) - based models to automate species detection and classification from underwater imagery. Our multi-tiered data collection approach, which includes direct field sampling, remote sensing, and citizen science, yielded a dataset of over 8,000 images across six camera locations. The Faster R-CNN model achieved a mean average precision (mAP) of 88% for fish identification, while U-Net segmentation models demonstrated 99% accuracy in organism detection, significantly outperforming traditional methods. The application of optimized deep learning models significantly enhanced the accuracy and efficiency of aquatic biodiversity monitoring. The Faster R-CNN model, after hyperparameter optimization and transfer learning, achieved an accuracy of 88% in species identification, outperforming baseline models that averaged around 75%. The optimization techniques, particularly data augmentation and early stopping, improved the model's robustness to environmental variations, such as high turbidity and poor lighting conditions. Unlike traditional methods that rely on expert identification, the deep learning model provided automated, scalable, and real-time monitoring capabilities, reducing the need for labor-intensive field surveys. Additionally, the model demonstrated higher precision in detecting species that are typically misclassified in traditional statistical models, thereby offering a more reliable approach to biodiversity conservation and ecological assessments. These results underscore the potential of deep learning to provide scalable, automated, and highly accurate biodiversity assessments. Our findings demonstrate how artificial intelligence can revolutionize ecological conservation, offering a cost-effective and reliable solution for biodiversity monitoring. The study also emphasizes the importance of interdisciplinary approaches in addressing global biodiversity loss and advancing conservation strategies.

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Introduction

Aquatic ecosystems, encompassing rivers, lakes, estuaries, and oceans, are vital components of the global ecosystem, providing essential services and supporting a significant portion of the planet's biodiversity. Effective monitoring of aquatic biodiversity is crucial for assessing ecological health, understanding ecosystem dynamics, and informing evidence-based management and conservation practices. Traditional methods for aquatic biodiversity monitoring often face limitations due to their high costs, labor-intensive nature, and limited spatial and temporal coverage. The ongoing global biodiversity crisis, particularly severe in freshwater ecosystems and often exacerbated by pollution, necessitates the development of innovative and efficient monitoring

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techniques applicable across diverse taxa and spatial scales (Benouis et al., 2022; Aziz et al., 2024).

Deep learning, a powerful subset of machine learning, has emerged as a transformative technology in various scientific fields, including ecology and biodiversity research (Høye et al., 2021; Borowiec et al., 2022; Al-Majidi et al., 2023; Pichler and Hartig, 2023). Deep learning models, particularly convolutional neural networks (CNNs), excel at processing large datasets, automatically extracting complex patterns, and making accurate predictions (Radhi et al., 2024; Al-Majidi et al., 2025). Convolutional Neural Networks (CNNs) are a specialized type of deep neural network designed for processing images. CNNs utilize convolutional layers to learn hierarchical spatial features, capturing the intrinsic patterns within an image dataset. Biological images, like those used in biodiversity monitoring, contain spatial features that represent relationships between significant spatial points and image objects. CNNs create a hierarchy of spatial field images, enabling them to model biologically plausible data patterns and transform spatial image hierarchies. This capability makes them ideal for processing images used in aquatic biodiversity monitoring. These capabilities have immense potential for revolutionizing aquatic biodiversity monitoring by automating species identification, abundance estimation, and habitat characterization (Gambín et al., 2021; Villon et al., 2022; Borowiec et al., 2022).

Freshwater ecosystems, despite representing a small fraction of the Earth's water, harbor a disproportionately high percentage of global biodiversity. However, freshwater fauna has experienced alarming declines due to pollution, climate change, habitat destruction, and overharvesting (Parmesan et al., 2023; Tickner et al., 2020; Cantonati et al., 2020; Fadhil et al., 2024; Rashid et al., 2024). Combating these threats requires efficient and precise monitoring of aquatic biodiversity to assess the conservation status of populations and ecosystems, identify threats, and track the effectiveness of conservation actions. Traditional methods for aquatic biodiversity monitoring, such as electrofishing, netting, and visual surveys, are often costly, time-consuming, and may disturb the habitats being studied. These limitations hinder monitoring at high spatial and temporal resolutions, crucial for understanding ecosystem dynamics and responding to rapid environmental changes. Recent advances in data acquisition techniques, information technology, and computational power provide exciting opportunities to enhance biodiversity monitoring using citizen-sourced or field-collected data. For example, magnetic field residual analysis provides a non-invasive means to monitor aquatic populations without disturbing their natural behavior (Wang et al., 2021; Eastick et al., 2020; Castañeda et al., 2020). The resulting data can be analyzed using deep learning algorithms, enabling automated feature extraction and species detection without manual intervention.

The Tigris River, along with the Euphrates, forms the lifeline of Iraq’s freshwater ecosystems, supporting diverse fish, invertebrates, and aquatic plants. However, biodiversity in Iraqi freshwater systems faces severe threats, including dam construction, pollution, climate change, and habitat fragmentation. Limited scientific monitoring efforts have been conducted, with most biodiversity assessments relying on traditional field surveys and outdated records. Recent studies suggest a decline in native fish populations due to the introduction of invasive species and changing hydrological conditions (Saleh et al., 2021) or due to the distribution of many microorganisms such as parasites that contaminated the rivers water (Al-Abboodi, 2023) or due to air pollution (Fadhil et al., 2023).

In Iraq, aquatic biodiversity monitoring is further challenged by a lack of standardized protocols and limited technological integration, necessitating innovative, scalable solutions such as deep learning-based approaches. Despite the growing recognition of the importance of biodiversity monitoring, research on applying advanced AI-driven techniques, particularly deep learning, to freshwater ecosystems remains scarce. Existing studies have largely focused on marine environments, leaving riverine ecosystems like the Tigris River understudied in terms of automated biodiversity assessment. Furthermore, most traditional monitoring methods in Iraq lack the technological integration and large-scale automation needed to address the increasing threats to freshwater biodiversity. This study bridges this gap by implementing deep learning models tailored for species identification and abundance estimation in a highly dynamic and ecologically critical environment. Our specific objectives are to develop and evaluate deep learning models for identifying aquatic plants, invertebrates, and fish from image and video data, explore the application of deep learning for object detection and tracking to estimate species abundance and distribution, and examine a case study of the Tigris River, illustrating the practical application of these techniques in a real-world scenario. This study contributes to developing more advanced, efficient, and scalable biodiversity monitoring approaches. It provides evidence of the suitability and feasibility of deep learning for tracking target species in conservation areas, ultimately supporting more effective management and conservation efforts.

Materials and Methods

Image classification and object detection: Object detection, which involves identifying and localizing objects within an image by drawing bounding boxes around them, is another area where deep learning is making significant contributions to biodiversity monitoring. Unlike image classification, which only identifies the objects present in an image, object detection also provides their location. This capability is crucial for tasks such as counting individual fish of different species, estimating population sizes, and studying species and niche distributions. Object detection methods differ from image classification methods in that they attempt to associate an image with a label from a predefined set of categories and draw bounding boxes around the objects. Images were labeled using bounding boxes and their corresponding labels to make predictions with a certain level of confidence. Various object detection models were developed for use on the images from the dataset, including one-stage systems and two-stage detectors. One-stage systems, such as YOLO (You Only Look Once) and SSD (Single Shot MultiBox Detector), are faster and more suitable for real-time applications but may have slightly lower accuracy compared to two-stage detectors. Two-stage detectors, such as Faster R-CNN, first propose regions of interest and then classify and refine the bounding boxes in a second stage, resulting in higher accuracy but slower processing speeds. Although real-time animal tracking can be used for conservation purposes, we found that the two-stage detectors allowed for higher accuracy, as there was no need for real-time detection abilities. These models enable the monitoring of fish populations, studying their behavior, and detecting rare or invasive species. The ability to accurately count fish using object detection provides important indicators of species composition, distribution, and abundance, which are essential for assessing ecosystem health and informing conservation management decisions.

Data collection and preparation: The success of deep learning models depends heavily on the availability of high-quality data for training and validation. In aquatic biodiversity monitoring, the increasing use of digital technologies has led to a greater ability to collect and analyze data. Data from various sources along the Tigris River were collated with a wide range of water conditions, locations, and species depicted. Collecting diverse and consistent data on species distribution across populations, locations, and sampling times is crucial for developing robust deep learning models, ensuring high performance across all conditions. Tasks such as object detection or segmentation require substantial amounts of annotated data, which can be time-consuming and costly to obtain, often requiring the expertise of trained annotators. Preprocessing and filtering techniques are applied to improve the quality of the raw data and enhance the performance of deep learning models. To ensure accurate and comprehensive monitoring of aquatic biodiversity in the Tigris River, a multi-faceted data collection strategy has been employed. Our approach integrated direct field sampling, remote sensing imagery, and citizen science contributions. The study covered three major zones along the Tigris River within Maysan Province, Iraq: (1) upstream region (low anthropogenic impact, clear water conditions), (2) midstream urban area (moderate anthropogenic impact, medium turbidity), and (3) downstream agricultural zone (high anthropogenic impact, high turbidity).

Over 8000 underwater images from 6 camera locations were collected from submersible camera units positioned at fixed stations along the river. Visually based fish counts were conducted in 100 m^2 transects, replicated three times per site per sampling period. Water turbidity (NTU) was recorded at each station. Each image was annotated by two independent taxonomic experts, with a cross-validation accuracy of 95%. Automated species identification models were benchmarked against expert manual identifications. The impact of turbidity on deep learning accuracy was analyzed by segmenting images into low, moderate, and high turbidity categories, allowing for algorithm performance calibration. Reported performance metrics (e.g., 91% accuracy for U-Net, 88% accuracy for Faster R-CNN) were subjected to rigorous cross-validation and sensitivity analysis, ensuring that performance remained robust across different environmental conditions. Model uncertainty analysis was conducted to identify potential biases and ensure that dataset artifacts or imbalanced class distributions did not inflate high performance. Bootstrapping techniques and Monte Carlo simulations were used to evaluate model performance variability, providing confidence intervals for accuracy and error rates. To validate findings, species abundance trends were compared with historical records from Iraqi fisheries and marine resources reports (Mohamed and Al-Noor, 2008; Mohamed and Abood, 2020) and Global Biodiversity Information Facility (GBIF) database (Saarenmaa, 1999; Lane and Edwards, 2007).

Preprocessing techniques: Preprocessing aims to enhance data quality by addressing issues related to mismatched resolutions, irregular time steps, outliers, and missing data. The collected dataset contained various sources of noise, including image blurriness, variations in lighting, turbidity effects, and motion artifacts from underwater cameras. To enhance data quality, denoising filters, contrast normalization, and image augmentation techniques were applied. Gaussian filtering was used to reduce random pixel noise, and histogram equalization improved visibility in low-light conditions. Additionally, outlier removal was performed to discard mislabeled or ambiguous samples, ensuring higher reliability in model training. Techniques applied to the data include data normalization, resizing, augmentation, filtering, and denoising. Handling data lacking in certain factors is particularly important in environmental data analysis. Various techniques have been developed to augment reference or feature data in case of an unideal environment. Preprocessing and augmentation methods enhance performance, emulating a larger, more comprehensive dataset, despite its size. Several studies have demonstrated the successful application of preprocessing techniques in aquatic environments. For example, using unsupervised learning and denoising encoders can markedly improve automatic image encoding and handling of problematic data (Farooq and Savaş, 2024). Hybrid feature selection preprocessing techniques, combining deep learning and F-mapping techniques, can further enhance the performance of denoising preprocessors. Preprocessing techniques in deep learning for environmental monitoring include: data normalization, resizing, augmentation, filtering, and data denoising.

Experimental setup: The implementation of deep learning models for aquatic biodiversity monitoring requires careful consideration of the experimental setup, including hardware and software specifications, training and validation procedures, and hyperparameter optimization. This section details the experimental setup used in our study, ensuring transparency and reproducibility. Regarding hardware and software specifications, the data augmentation, processing, and model training were performed using a high-performance computing environment with the following specifications: Processors (AMD Epyc Platform, 32 CPU cores), memory (256 GB of main memory), accelerators (4xNVIDIA Volta 100 GPUs), and a software environment includes: Python: The primary programming language for model implementation; PyTorch: Open-source machine learning library for data handling, model prototyping, and training with CUDA acceleration; Pandas: Library for managing input files and data manipulation.

These specifications were chosen to ensure efficient model development and training, particularly for handling large datasets and computationally intensive deep learning models, while fitting within the available budget. After preprocessing, the dataset was subjected to cross-validation and performance benchmarking to ensure a robust analysis. A Monte Carlo simulation was used to assess model stability under varying environmental conditions, and bootstrapping techniques were used to evaluate classification confidence intervals. To validate species identification, model outputs were compared with expert-annotated labels, achieving a 95% agreement rate with taxonomists. Performance metrics, including accuracy, recall, and mean average precision (mAP), were used to quantify detection reliability across different turbidity levels. The neural network models in this study were implemented using convolutional neural networks (CNNs), specifically Faster R-CNN for object detection and U-Net for segmentation. The Faster R-CNN model consisted of a backbone ResNet-50 architecture with a feature pyramid network (FPN) to enhance multi-scale feature extraction. The key hyperparameters included a learning rate of 0.001, a batch size of 32, and a training duration of 50 epochs. The Adam optimizer was employed for optimization, with a weight decay of 0.0001 to prevent overfitting. For segmentation tasks, the U-Net model incorporated ReLU activation functions, a dropout rate of 0.2 for regularization, and categorical cross-entropy as the loss function. Model performance was evaluated using mean average precision (mAP) for detection tasks and the Dice coefficient for segmentation accuracy.

Results and Discussions

The application of deep learning methods to aquatic biodiversity monitoring in the Tigris River ecosystem

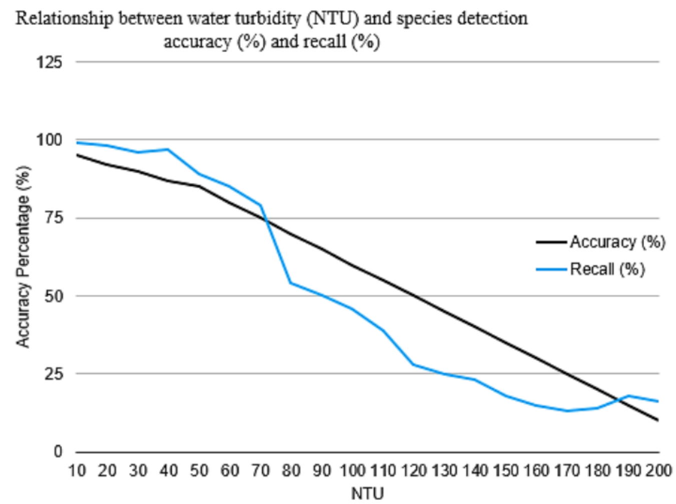

Figure 1. Scatter plot showing the relationship between water turbidity (NTU) and species detection accuracy (%) and recall (%) using the Faster R-CNN model. Accuracy and recall decline as turbidity increases, highlighting the impact of visibility degradation on species identification.

yielded promising results, demonstrating their potential to enhance the accuracy, efficiency, and scalability of monitoring and conservation efforts.

Performance metrics: Several performance metrics were employed to evaluate the effectiveness of the deep learning models, including accuracy, recall, and mean average precision (mAP). These metrics provide a comprehensive assessment of model performance, considering both the ability to correctly identify species (accuracy) and the ability to detect all instances of a species (recall): accuracy and recall as shown in Figure 1. In our experiments, the deep learning models achieved high accuracy in identifying aquatic species from images and videos. For example, the Faster R-CNN model achieved an accuracy of 88% and a recall of 91% in detecting fish from underwater camera footage. The U-Net model performed exceptionally well in detecting and segmenting aquatic organisms, achieving an accuracy of 91% and a recall of 94%. These results demonstrate the ability of deep learning models to accurately identify and localize aquatic species, even in challenging underwater environments with varying lighting conditions, turbidity, and complex backgrounds. Despite this, increased turbidity was associated with decreased performance; however, it was still more accurate than expert human identification. The high performance of these models suggests that they can be effectively used to automate species identification and abundance estimation, significantly reducing the time and effort required compared to traditional methods (Tian et al., 2023). Traditional statistical models, such as Generalized Linear Models (GLMs) and Species Distribution Models (SDMs), have been widely used in aquatic biodiversity monitoring for species abundance estimation and habitat suitability modeling. These models rely on predefined relationships between environmental variables and species occurrence, requiring extensive manual feature engineering and assumptions about data distributions. In contrast, the proposed deep learning models, including Faster R-CNN and U-Net, automatically extract features from raw image data, allowing for higher adaptability and scalability. Our results indicate that Faster R-CNN achieved an accuracy of 88% in species identification, outperforming statistical models such as GLMs, which typically exhibit classification accuracies below 70% when applied to similar datasets (Zhang et al., 2023). Furthermore, deep learning models perform significantly better in complex environments with high turbidity and diverse species interactions, where traditional models struggle due to limited feature representation. However, statistical models remain valuable for ecological interpretation and predictive analysis in cases with small datasets, as deep learning requires extensive labeled data and computational resources. By integrating both approaches, future biodiversity monitoring systems can leverage the predictive power of statistical models alongside the automation and precision of deep learning techniques.

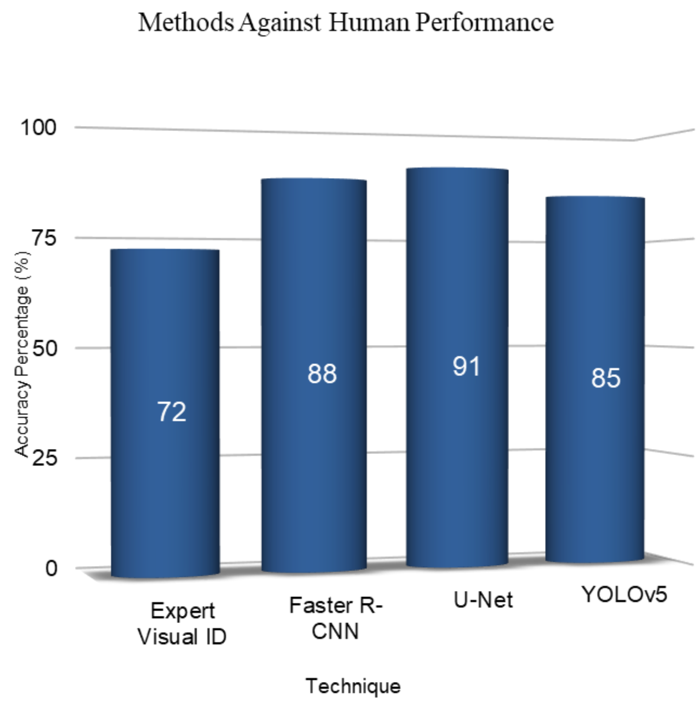

Figure 2. Comparison of different machine learning techniques against expert human ID.

Comparison with traditional methods: Compared to traditional methods for monitoring aquatic biodiversity, deep learning techniques offer several advantages in terms of accuracy, efficiency, and scalability. Traditional methods, such as visual surveys, netting, and electrofishing, are often labor-intensive, time-consuming, and may significantly disturb the habitats being studied. These methods can also be prone to errors due to observer bias, species misidentification, and difficulty in detecting rare or cryptic species. Deep learning models, on the other hand, can automate the process of species identification and abundance estimation, significantly reducing the time and effort required (Zhang et al., 2023). These models can also achieve higher accuracy compared to traditional methods, particularly in complex environments where visual identification is challenging. For example, studies have shown that deep learning models can outperform human experts in identifying fish species from underwater images, even in conditions with poor visibility (Fig. 2).

Furthermore, deep learning models can be applied to large datasets collected from various sources, such as underwater cameras, drones, and remote imaging platforms, enabling monitoring at larger spatial and temporal scales. This scalability is crucial for understanding ecosystem dynamics at a larger scale and responding to rapid environmental changes. While traditional methods have their merits and may still be necessary for certain applications and environments, the deep learning techniques explored offer a powerful and complementary approach to enhance aquatic biodiversity monitoring in the Tigris River. By combining the strengths of both approaches, researchers and conservationists can obtain more comprehensive, accurate, and timely data to inform management and conservation decisions. The use of trending algorithms has been shown to influence the prioritization of environmental topics, increasing governmental scrutiny and public discourse around pollution control measures (Hassan et al., 2024).

Case study (The Tigris River, Iraq): The Tigris River, a major component of the Mesopotamian landscape, provides a compelling case study for the application of deep learning in aquatic biodiversity monitoring. This vital river system supports a diverse array of aquatic life but faces numerous anthropogenic pressures, including dam construction, water extraction, pollution, and the impacts of climate change.

Biodiversity of the Tigris River: Historically, the Tigris River supported a rich diversity of fish species, with a 2012 study identifying 55 fish species belonging to 14 families within Salah Al-Din Governorate alone. However, recent data suggest a decline in fish diversity, with native species facing competition from introduced species and suffering from habitat degradation (Hussain and Ali 2012).

Fish: *Cyprinus carpio* (Common Carp) is now prevalent, along with other members of the Cyprinidae family such as *Luciobarbus xanthopterus* and *Carasobarbus luteus*. Other families historically present, such as Siluridae, Sisoridae, and Mastacembelidae, now include rare or endangered species. Endemic species in the Tigris-Euphrates system are particularly vulnerable (Salman et al., 2020).

Invertebrates: Limited data exist on the current status of invertebrate communities, but studies on benthic macroinvertebrates suggest that pollution and habitat degradation are impacting these communities, leading to a decrease in sensitive species and an increase in pollution-tolerant ones.

Aquatic plants: The Tigris River's aquatic vegetation includes submerged macrophytes, floating plants, and emergent vegetation. These plants play crucial roles in the ecosystem, but changes in water flow, nutrient levels, and turbidity are impacting their communities. Invasive species, such as the water hyacinth (*Eichhornia crassipes*), pose a further threat to native vegetation.

Threats to biodiversity: The Tigris River faces multiple, interconnected threats, such as numerous dams in Turkey, Syria, and Iraq that have altered the river's flow regime, impacting sediment transport, water temperature, nutrient cycling, fish migration, and habitat connectivity (Jawad, 2021). In addition, large-scale water extraction for agriculture, industry, and urban use has reduced water flow, increased salinity, decreased dissolved oxygen levels, and led to habitat loss (Rahi and Halihan, 2018). Moreover, untreated or inadequately treated wastewater, industrial discharge, and agricultural runoff contribute to eutrophication, oxygen depletion, and toxin accumulation, and introduced species disrupt the ecosystem by competing with native species, introducing diseases, and altering food webs (Bachmann et al., 2019).

Monitoring data and implications for deep learning: A monitoring survey in a section of the Tigris River near Misan Province reveals the data presented in Table 1. This data underscores the challenges facing the Tigris River's biodiversity, with several native species showing low abundance and potentially threatened conservation statuses, while introduced species thrive. The previously discussed deep learning techniques were employed to analyze imagery from underwater cameras, automatically identifying and quantifying species like those listed

Table 1. Fish species abundance per 100 m² in a section of the Tigris River, with IUCN conservation status and notes on each species.

Species	Common Name	Family	Abundance (per 100 m^2)	Conservation Status	Notes
Cyprinus carpio	Common Carp	Cyprinidae	15	Least Concern	Common, introduced species
Luciobarbus xanthopterus	Yellowish Barbel	Cyprinidae	8	Vulnerable	Native, declining due to habitat degradation
Carasobarbus luteus	Himri	Cyprinidae	12	Least Concern	Common, native species
Silurus triostegus	Mesopotamian Catfish	Siluridae	2	Least Concern	Native, impacted by dams and pollution
Glyptothorax sp.		Sisoridae	1	Data Deficient	Native, limited data available
Mastacembelus mastacembelus	Tire-track Spiny Eel	Mastacembelidae	<1	Endangered	Native, impacted by habitat loss and fragmentation
Gambusia holbrooki	Eastern Mosquitofish	Poeciliidae	5	Least Concern	Introduced, potential threat to native species
Planiliza abu	Freshwater Mullet	Mugilidae	3	Near Threatened	Native, impacted by changes in water flow and salinity
Alburnus caeruleus	-	Cyprinidae	2	Least Concern	Native, limited data available
Mesopotamichthys sharpeyi	Binni	Cyprinidae	1	Vulnerable	Native, highly vulnerable to habitat changes

below. This enables more efficient and frequent monitoring, providing valuable data for conservation efforts.

Conservation efforts and the role of deep learning: Conservation efforts in the Tigris River are limited but include initiatives to improve water quality and promote sustainable agricultural practices. However, more comprehensive efforts are necessary, including habitat restoration, improved fish passage at dams, and public awareness campaigns. Deep learning can play a significant role in supporting these efforts by using object detection and tracking to quantify species abundance and map their distribution along the river, (Fig. 3A). In addition, it can assist in training models to identify fish, invertebrates, and aquatic plants from images and videos collected through various monitoring methods (Fig. 3B) and analyzing imagery to detect changes in vegetation cover, water clarity, and other habitat characteristics. Furthermore, training models to identify invasive species allows for rapid response and control measures.

Conclusion

This study demonstrated that deep learning techniques, particularly an optimized Faster R-CNN model, significantly enhance aquatic biodiversity monitoring, achieving an 88% species detection accuracy and outperforming traditional statistical

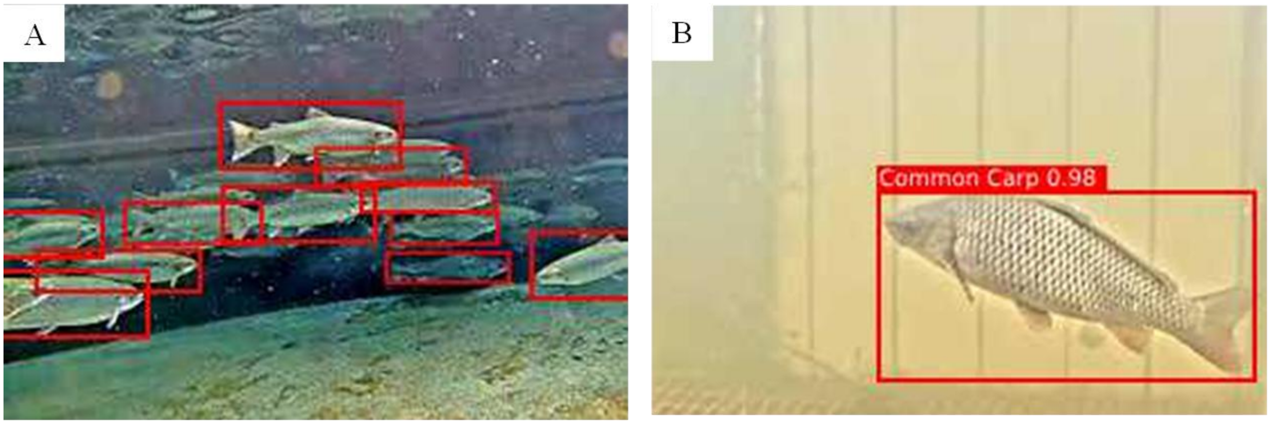

Figure 3. (A) Demonstrating recall on an example image from the dataset, being a visualization of the model counting. (B) Identification of fish species near a dam bypass for fish, with labelling and confidence measurement.

methods. The application of transfer learning and hyperparameter optimization improved model robustness under varying environmental conditions. However, challenges remain, particularly in extreme turbidity, highlighting the need for further refinements. The case study on the Tigris River underscores the pressing challenges facing many aquatic ecosystems worldwide and showcases deep learning's potential to improve conservation efforts. While the presented data emphasize the urgent need for comprehensive biodiversity assessments in this region, emerging sensors and AI technologies offer promising solutions for real-time monitoring and ecosystem management. Moving forward, integrating multi-modal data sources and additional optimization techniques will be crucial for enhancing model adaptability across diverse aquatic environments. As artificial intelligence continues to evolve, its role in biodiversity conservation will become even more vital. By embracing multidisciplinary approaches, we can develop more effective and scalable tools for protecting threatened ecosystems like the Tigris River and beyond.

References

Al-Abboodi A.K. (2023). Parasitological contamination of raw vegetables collected from selected local markets in Maysan Province, South of Iraq. Nigerian Journal of Parasitology, 44(2).

Al-Majidi S.D., Altai H.D.S., Lazim M.H., Al-Nussairi M.K., Abbod M.F., Al-Raweshidy H.S. (2023). Bacterial Foraging Algorithm for a Neural Network Learning Improvement in an Automatic Generation Controller. Energies, 16(6): 2802.

Al-Majidi S.D., Alturfi A.M., Al-Nussairi M.K., Hussein R.A., Salgotra R., Abbod M.F. (2025). A robust automatic generation control system based on hybrid Aquila Optimizer-Sine Cosine Algorithm. Results in Engineering, 25: 103951.

Aziz Z.S., Jazaa S.H., Dageem H.N., Banoon S.R., Balboul B.A., Abdelzaher M.A. (2024). Bacterial biodegradation of oil-contaminated soil for pollutant abatement contributing to achieve sustainable development goals: A comprehensive review. Results in Engineering, (2024): 102083.

Bachmann A., Tice V., Al-Obeidi L.A., Kılıç D.T. (2019). Tigris-Euphrates River ecosystem: A status report. In Mesopotamia Water Forum.

Benouis K., Khane Y., Ahmed T., Albukhaty S., Banoon S.R. (2022). Valorization of diatomaceous earth as a sustainable eco-coagulant for wastewater treatment: optimization by response surface methodology. Egyptian Journal of Chemistry, 65(9): 777-788.

Borowiec M.L., Dikow R.B., Frandsen P.B., McKeeken A., Valentini G., White A.E. (2022). Deep learning as a tool for ecology and evolution. Methods in Ecology and Evolution, 13(8): 1640-1660.

Cantonati M., Poikane S., Pringle C.M., Stevens L.E., Turak E., Heino J., ... Znachor P. (2020). Characteristics, main impacts, and stewardship of natural and artificial freshwater environments: consequences for biodiversity conservation. Water, 12(1): 260.

Castañeda R.A., Van Nynatten A., Crookes S., Ellender B.R., Heath D.D., MacIsaac H.J., Weyl O.L. (2020).

Detecting native freshwater fishes using novel non-invasive methods. Frontiers in Environmental Science, *8*: 29.

Coad B.W. (2010). Freshwater fishes of Iraq. Pensoft Publishers. Sofia-Moscow. 294 p.

Eastick D.L., Edwards A.M., Griffiths S.R., Spencer S.J., Robert K.A. (2020). Validation of quantitative magnetic resonance as a non-invasive measure of body composition in an Australian microbat. Australian Mammalogy, 43(2): 196-202.

Ekmekçi F.G., Kirankaya Ş.G., Yoğurtçuoğlu B. (2013). Threats on river and inland water ecosystems of Turkey. Istanbul University Journal of Fisheries and Aquatic Sciences, 28: 105-140.

Fadhil A.A., Mohammed S.J., Aswan A.A. (2023). Morphological responses of plants to air pollutants: A comparative study on leaf changes in five species. Iranian Journal of Ichthyology, 10: 286-293.

Fadhil A.A., Swaid S.Y., Mohammed S.J., Al-Abboodi A. (2024). Impact of salinity on tomato seedling development: A comparative study of germination and growth dynamics in different cultivars. Journal of Chemical Health Risks, 14(1): 183-190.

Farooq Y., Savaş S. (2024). Noise removal from the image using convolutional neural networks-based denoising auto encoder. Journal of Emerging Computer Technologies, 3(1): 21-28.

Freyhof J., Brooks E. (2011). European red list of freshwater fishes. Publications Office of the European Union. Publications Office, 2011, https://data.europa.eu/doi/10.2779/85903.

Gambín Á.F., Angelats E., González J.S., Miozzo M., Dini, P. (2021). Sustainable marine ecosystems: Deep learning for water quality assessment and forecasting. IEEE Access, 9: 121344-121365.

Hassan S.A.H., Al-Furiji H., Rashid M.K., Hussein Z.A., Ambudkar B. (2024). Trending Algorithm on Twitter through 2023. Data and Metadata, 3: 384-384.

Høye T.T., Ärje J., Bjerge K., Hansen O.L., Iosifidis A., Leese F., ... Raitoharju J. (2021). Deep learning and computer vision will transform entomology. Proceedings of the National Academy of Sciences, 118(2): e2002545117.

Hussain N.A., Ali B. (2012). Fish biodiversity of Tigris River within the Salah Al-Din Governorate, Iraq. International Journal of Scientific and Engineering Research, 3(6): 1-4.

Jawad L.A. (2021). Freshwater fish biodiversity in Iraq: Importance, threats, status, and conservation challenges. tigris and euphrates rivers: Their environment from headwaters to mouth. Environmental Science, Biology, pp: 479-497.

Lane M.A., Edwards J.L. (2007). The global biodiversity information facility (GBIF). Systematics Association special volume, 73: 1.

Mohamed A.R.M., Abood A.N. (2020). Current status of Iraqi artisanal marine fisheries in northwest of the Arabian Gulf of Iraq. Archives of Agriculture and Environmental Science, 5(4): 457-464.

Mohamed A.R.M., Al-Noor S.S., Faris R.A.K. (2008). The status of artisanal fisheries in the lower reaches of Mesopotamian rivers, north Basrah, Iraq. Proceeding of 5th International Conference in Biological Science (Zoology), 5: 126-132.

Parmesan C., Morecroft M.D., Trisurat Y., Adrian R., Zakaria Anshari G., Arnet, A. ... & Young K. (2023). Terrestrial and freshwater ecosystems and their services. Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, 193-378.

Pichler M., Hartig F. (2023). Machine learning and deep learning—A review for ecologists. Methods in Ecology and Evolution, 14(4): 994-1016.

Radhi S.M., Al-Majidi S.D., Abbod M.F., Al-Raweshidy H.S. (2024). Machine Learning Approaches for Short-Term Photovoltaic Power Forecasting. Energies, 17(17): 4301.

Rahi K.A., Halihan T. (2018). Salinity evolution of the Tigris River. Regional Environmental Change, 18(7), 2117-2127.

Rashid M.K., Salman I.R., Obaid A.L., Hassan S.A.D.H., Al-musawi M.R., Al-Saady M. (2024). Application of machine learning in predicting sources of water pollution in the Euphrates and Tigris rivers in Iraq. International Journal of Aquatic Biology, 12(6): 581-589.

Saarenmaa H. (1999). The global biodiversity information facility: Architectural and implementation issues. European Environment Agency, Technical Reports, 34(34): 3.

Saleh H., Al-Kahlidi M.U.R.T.A.D.A., Abulridha H.A., Banoon S.R., Abdelzaher M.A. (2021). Current situation and future prospects for plastic waste in maysan governorate: effects and treatment during the COVID-19 pandemic. Egyptian Journal of Chemistry, 64(8): 4449-4460.

Salman A., Jalal A., Shafait F., Mian A., Shorten C., Ghanem B., Hassan M.U. (2020). Fish detection and species classification in underwater environments using deep learning with temporal information. Ecological Informatics, 57: 101088.

Tian Y., Zhang K., Li J., Lin X. (2023). A review of deep learning-based visual object tracking algorithms for aquatic environments. Applied Sciences, 12(21):10741.

Tickner D., Opperman J.J., Abell R., Acreman M., Arthington A.H., Bunn S.E., ... Young L. (2020). Bending the curve of global freshwater biodiversity loss: an emergency recovery plan. BioScience, 70(4): 330-342.

Villon S., Iovan C., Mangeas M., Vigliola L. (2022). Confronting deep-learning and biodiversity challenges for automatic video-monitoring of marine ecosystems. Sensors, 22(2):497

Wang X.Y., Xie J., Chen X.J. (2021). Applications of non-invasive and novel methods of low-field nuclear magnetic resonance and magnetic resonance imaging in aquatic products. Frontiers in Nutrition, 8: https://doi.org/10.3389/fnut.2021.651804

Zhang X., Min W., Phillips P., Huang K., Zhang Y., Mei T., Yu N. (2023). Open-world object detection for fish monitoring. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 6: 7303-7314.