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SMART FISH PASSAGE DESIGN AND APPLICATION OF HYDROACOUSTIC COMMUNICATION TECHNOLOGY IN AQUATIC ECOSYSTEM RESTORATION

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Abstract. The demand for creative solutions to help migrate fish and conservation efforts grows as aquatic environments experience more and more pressure from humans and fragmentation of habitat. The utilization of hydroacoustic technology for communication in conjunction with smart fish pathway architecture is the main emphasis of this research to improve rehabilitation efforts for aquatic environments. Using sophisticated systems for tracking and regulation to improve migratory pathways, the study investigates cutting-edge solutions in engineering for fish passage. Real-time data capture and transmission are made possible by the application of hydroacoustic technology for communication, which means that fish populations and monitoring systems can effectively communicate. The creation of intelligent fish passage structures with actuators, sensors, and communications components is a major focus of the research. The best passage efficiency of these structures is ensured by their dynamic adaptation to fish behavior and variables in the environment. An essential interface for gathering information on behavior, evaluating migratory trends, and putting adaptive management plans into practice is hydroacoustic communications technology. In order to assess the efficacy of the hydroacoustic communication technology and smart fish passage design in a variety of aquatic habitats, a thorough field investigation is part of the suggested methodology. To evaluate the effect on migration of fish rates of achievement, species diversity, and general well-being of the ecosystem, field data will be studied.

Key words: Marine Internet of Things; Internet of Underwater Things; protocols; smart fish, passage, hydroacoustic communications, aquatic ecosystem restoration

1. Introduction. In recent times, Earth observation, alterations in marine ecosystems, and changing climates have garnered human interest and have had a major effect on human productivity[8]. Underwater recognition of targets is currently a growing field of study due to the increasing demand for underwater identification. It has applications in the areas of ship noise categorization [7], underwater target localization and recognition [15], and aquatic environment surveying and demonstrating [14]. Underwater target recognition has new opportunities due to the rapid growth of artificial intelligence methods like machine learning and deep learning, the development of supercomputing, the substantial rise in math authority, and the rapid expansion of big-data-processing computation.

Researchers in this field are swiftly implementing research findings to improve technological iterations. Nevertheless, challenges remain in the application of deep learning for underwater target recognition, including small data amounts, limited flexibility of traditional visual system computations, complex pre-processing procedures, and deep learning patterns that are still too intricate to offer excellent generalizability. It is worth noting that acoustic and various signal-filtering techniques are useful for detecting pipeline leaks, and that deep learning algorithms are also widely employed, suggesting that models based on deep learning have excellent generality and swear in underwater acoustics [11].

To deploy IoUT, follow these three steps [24]. Developing a dynamic, ongoing, all-encompassing, and intelligent real-time view of the underwater world is the first stage. Large-scale, long-term, continuous oceanographic data collection has been made possible in recent decades by underwater sensor networks made up of a range of equipment, including conductivity, and heat and depth detectors, microbial sensors, and current meters [6]. Innovative uses that utilize human–robot interactions, such as undersea pipeline assessment, undersea volcanic

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activity and hydrothermal source research, seabed visualisation, strategic surveillance, and underwater rescue, are driving up demand for real-time multimedia data [22].

Large-scale real-time underwater data transmission is the second phase of the IoUT deployment. Undersea gliders, remotely controlled unmanned underwater vehicles (ROVs), and automated unmanned underwater vehicles (UUVs) are examples of movable systems that have made it possible to build mobile underwater networks and are essential for high-quality surveillance footage [26, 27, 17, 19]. The smart analysis of large amounts of underwater data is the third step in the deployment of IoUT. The amount of maritime data that was acquired in the past was limited because of a lack of equipment and minimal investment, which caused the process to take years or months.

The motivation behind this research stems from the ever-increasing need for innovative solutions to address the challenges faced by aquatic environments due to human activities and habitat fragmentation. As human impact on aquatic ecosystems intensifies, it becomes imperative to find creative and effective ways to support fish migration and conservation efforts. This research is driven by the pressing demand to enhance the rehabilitation of aquatic environments, offering a lifeline to struggling fish populations.

This study focuses on a novel approach that combines hydroacoustic technology with smart fish pathway architecture to revolutionize the way we facilitate fish migration and conservation. By harnessing cutting-edge engineering solutions, including real-time data capture and transmission through hydroacoustic technology, we enable seamless communication between fish populations and monitoring systems. The novelty lies in the creation of intelligent fish passage structures equipped with advanced actuators, sensors, and communication components, allowing them to adapt to fish behavior and changing environmental conditions dynamically.

The main contribution of the proposed method is given below:

1. Using hydroacoustic data, a DNN-LSTM model is trained to identify complex temporal correlations in fish movements.
2. The trained model is then included into the smart fish passageways control system, enabling ongoing adaptation in response to change fish behavior and environmental variables.
3. The goal of the study is to show how DNN-LSTM can be used to provide fish passage systems with a smart, self-learning framework that minimizes ecological disturbance while maintaining efficient passage.

Remaining sections of this paper are structured as follows: Section 2 discusses about the related research works, Section 3 describes the Smart fish passage design, application of hydroacoustic communication technologyand Deep Neural Networks, Section 4 discusses about the experimented results and comparison and Section 6 concludes the proposed optimization method with future work.

2. Related Works. The future's top innovations for implementing smart data processing on massive scales will be big data, cloud computing, artificial intelligence, and virtual reality [18]. Therefore, one of the key areas of research for upcoming applications of human-robot interaction is the real-time changing and visual tracking of underwater landscapes. Most commercial marine IoT applications concentrate on both surface and subsea IoT technology to measure and monitor business activity. It is possible to identify and isolate the IoUT market sector for usage in aquaculture and fishing, that works with fish breeding in small spaces [5].

In response, the central server analyzes the information and creates management and choice-making strategies. Large-scale fish and marine creature searches and analyses in open waterbodies comprise another set of tasks [28, 23, 12, 2]. It should be noted that the notion of Internet of Things Ocean (IoTO) [10] or Ocean of Things is mentioned in the literature in addition to Internet of Things (IoUT). One way to conceptualize the Internet of Things (IoT) technology is as an intelligent underwater item network. One potential technique for the organized administration of various marine data types is IoTO.

The International Maritime Organization (IMO) first established the concept of "e-Navigation" [13, 21] to enable different kinds of navigation services, which is akin to Maritime IoT and was intended to improve the shipping sector. Other services were subsequently added; these are mentioned above. Thus, maritime IoT refers to a dispersed hardware–software complex that allows for transmitted from different above-water ocean engineering structures and items gadgets, used via a unified machine-type communication via a data system (typically the Internet, or a marine information network, or a network of underwater services).

The wavelet transform approach is not without flaws, though. The shortcomings of various discrete wavelet

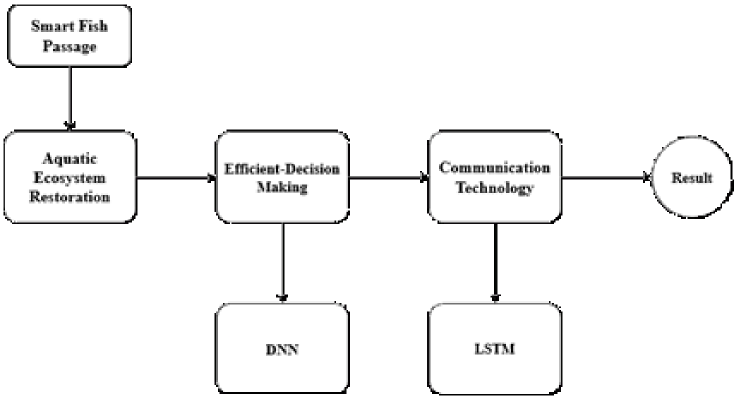

Fig. 3.1: Architecture of proposed method

transform (DWT) system designs were noted by author in [3, 9]. The outstanding characteristics of the wavelet transform (WT) in one dimension are not transferable to two dimensions or higher, and it shows a lack of adaptivity to additional modality disintegration techniques, such as EMD, LMD, VMD, SGMD, etc. The one-dimensional characteristic vector obtained by the wavelet transform is frequently not enough to provide optimal features because of the intricate nature of the hydroacoustic surroundings [1]; therefore, finding a way to enhance the selection of multidimensional or optimal features has emerged as a potential area of research.

To reclaim the breakpoints in the LOFAR spectrum and achieve an exceptional identification rate in the CNN network, the author [25] developed a multi-step decision-algorithm-based improvement technique based on LOFAR spectrum improvement for underwater detection of targets. After implementing these spectrograms into the AlexNet network, the researchers [20, 16, 4] analyzed typical spectrum maps, such as LOFAR, Audio, The demon, a histogram etc. and discovered that the LOFAR spectra had the best identification rate.

The wavelet transform approach, particularly the discrete wavelet transform (DWT) system designs, has been found to have shortcomings in handling multidimensional data. While it may perform well in one dimension, it lacks adaptivity when applied to two or more dimensions. This limitation hinders its effectiveness in dealing with the complex nature of hydroacoustic environments, where multidimensional data is often encountered. The one-dimensional characteristic vector obtained from the wavelet transform may not provide optimal features for underwater target detection due to the intricate nature of hydroacoustic surroundings. This inadequacy highlights the need for improved techniques to select multidimensional or optimal features that can better capture the nuances of the underwater environment.

3. Proposed Methodology. The proposed methodology uses deep learning method for Smart fish passage design and application of hydroacoustic communication technology in aquatic ecosystem restoration. It uses Deep Neural Networks based Long-Short Term Memory (LSTM) for smart fish passages and intelligent decision-making. Field tests in various aquatic habitats will be carried out to evaluate the effectiveness of the smart fish tunnels augmented by DNN-LSTM. The general effect on the recovery of aquatic ecosystems, species-specific adaptation, and migration success rates are examples of key performance indicators. The goal of the study is to show how DNN-LSTM can be used to provide fish passage systems with an intelligent, self-learning architecture that minimizes ecological disturbance while maintaining efficient passage. In figure 3.1 shows the architecture of proposed methodology.

3.1. Smart Fish Passage and hydroacoustic communication for Aquatic Restoration. With the overall objective of fostering successful aquatic ecosystem restoration, this research focuses on the integration of Deep Neural Networks (DNN) and Long Short-Term Memory (LSTM) networks to create an intelligent system for smart fish passage design and hydroacoustic communication. Through real-time, data-driven communication between fish populations and fish passage structures, the study hopes to improve the responsiveness and flexibility of fish passage structures by utilizing the temporal learning capabilities of DNN-LSTM architectures.

The suggested approach uses hydroacoustic data to train a DNN-LSTM model, which then uses the data to capture and evaluate the complex temporal dynamics of fish movement patterns. The trained model is the central intelligence element of smart fish passageways, allowing for dynamic modifications based on the hydroacoustic monitoring system's real-time data. At the same time, a bidirectional communication channel is established between the fish community and the smart channels using hydroacoustic communication technology.

A variety of aquatic conditions will be used for field testing to assess how well the DNN-LSTM-based smart fish passage system works. To verify the efficacy of the suggested strategy, important indicators like ecological impact, species-specific adaptation, and migration success rates will be evaluated. The goal of the study is to show how DNN-LSTM can be an effective tool for developing smart, self-learning fish passage solutions that maximize fish migration and ecosystem restoration initiatives.

The results obtained from this study have wider ramifications for the development of technology-based conservation tactics. The suggested framework demonstrates a comprehensive strategy for improving aquatic ecosystems by fusing deep learning methods with hydroacoustic communication, tackling the problems brought on by habitat destruction and dispersion. The findings highlight the possibility for innovative technologies to play a critical role in the ecological restoration of aquatic ecosystems and add to the expanding field of intelligent ecological management and monitoring.

3.2. Deep Neural Networks (DNN). Artificial neural networks that analyze data using numerous layers—hence the name "deep"—are known as deep neural networks (DNNs). Nodes, sometimes referred to as neurons or units, are present in every layer of the network and are connected by weighted connections. Deep neural networks (DNNs) are a subclass of machine learning models that fall within the deep learning category.

To enable them to learn hierarchical data representations, DNNs usually consist of numerous hidden layers positioned among the input and output layers. The network can catch intricate patterns and characteristics because of its depth. Backpropagation is an optimization algorithm used in DNN training. Through training, the network attempts to reduce the discrepancy between target values and projected outputs by adjusting the weights of its connections.

Activation functions are applied by nodes in each layer to the weighted total of their inputs. Sigmoid, hyperbolic tangent (tanh), and rectified linear unit (ReLU) are examples of common activation functions. By adding non-linearity to the system, these functions enable it to learn intricate mappings. Several deep learning structures, including TensorFlow, PyTorch, Keras, and others, are used to implement DNNs. Deep learning model construction, training, and deployment tools are offered by these platforms.

Natural language processing, recommendation systems, picture and speech recognition, and other industries have shown impressive performance using DNNs. When given tasks that require a lot of data to be trained, they perform exceptionally well. Large volumes of labeled data are needed for the computationally demanding process of training deep neural networks. Another frequent issue which must be handled is overfitting, which occurs when a model learns noise in the data used for training rather than the real patterns.

3.3. Long-Short Term Memory (LSTM). One kind of recurrent neural network (RNN) architecture called Long Short-Term Memory (LSTM) was created to solve the gradient that diminishes issue, which is a prevalent problem with conventional RNNs. LSTMs are especially useful for problems requiring time-series data, processing natural languages, and sequential pattern identification since they were developed to recognize dependencies that persist in sequential data.

The capacity of LSTMs to preserve cells with memories which can store and retrieving information across extended sequences is essential for avoiding the loss of pertinent data during training. This is made possible by a group of gates that control information flow into, out of, and inside the memory cell. These gates include an input gate, an output gate, and a forget gate.

Cell State (Ct): The long-term information storage cell in the memory.

The output generated by the LSTM at a specific time step is known as the Hidden State (Ht).

How much of the new data should be saved in the memory cell is decided by the input gate (i).

The Forget Gate (f) determines the amount of data that should be removed from the memory cell. The output gate (o) controls the amount of memory cell content that is utilized to produce the output.

Long-term dependency capture is a key component of LSTMs' performance in a variety of uses, such as time-series prediction, translation by machine, and speech recognition. An LSTM could be used to simulate

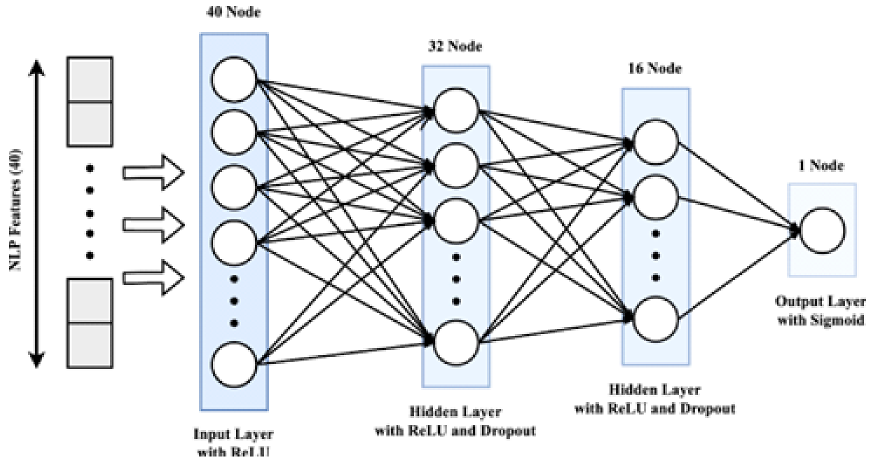

Fig. 3.2: Structure of DNN-LSTM

and foresee the actions of fish over time in the context of your mentioned study on hydroacoustic communication technology and smart fish passage design. This would allow the smart travel structures to change their configuration based on the evolving patterns seen in the hydroacoustic data. In figure 3.2 shows the structure of DNN-LSTM.

Hydroacoustic technology allows for non-intrusive monitoring of fish populations without physically disturbing their habitat. This is in contrast to some traditional methods like electrofishing, which can be invasive. It can cover large areas, making them suitable for monitoring fish migration in expansive aquatic environments such as rivers, lakes, and oceans. This wide coverage is often difficult to achieve with manual methods. They provide real-time data, allowing researchers to track fish movements and behaviors as they occur. This immediacy can be crucial for making timely management decisions.

Hydroacoustic systems can distinguish between different fish species based on their acoustic signatures. This capability is valuable for studying specific species' migration patterns and behaviours. Compared to physical interventions like fish ladders or traps, hydroacoustic technology typically has a lower ecological impact since it does not require altering the natural flow of water or physical structures.

4. Result Analysis. Although short-time Fourier, Meier, Hilbert-Yellow, and additional methods of processing have been put forth to address some aspects of indicate extraction of features, single signal processing for feature extraction is no longer able to increase the classifier's effectiveness due to the flaws in the various algorithms. Therefore, one path for the advancement of hydroacoustic signal detection will be multi-spectrum feature fusion. The dataset is taken from Kaagle for evaluation.

The evaluation parameters such as accuracy, precision, recall and f1-socre is measured. The proposed method achieves better result in all parameter metrics.

The simulation's accuracy, which is expressed as follows in Equation (4.1), indicates how effectively the model works across classes.

$$Accuracy = \frac{Total\ number\ of\ truly\ classified\ samples}{Total\ Samples} \tag{4.1}$$

The precision of the simulations is an assessment of their capacity to detect true positives, and it is computed using Equation (4.2).

$$Precision = \frac{TP}{TP + FP} \tag{4.2}$$

The proportion of projected true positive and false negative values to true positive prediction values is

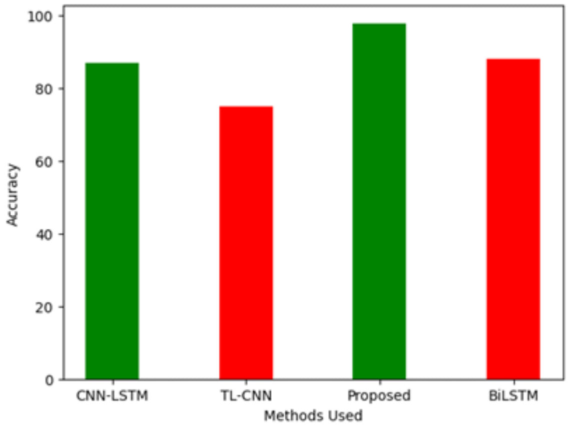

Fig. 4.1: Accuracy

known as the recall. Equation (4.3) represents the calculation.

$$Recall = \frac{TP}{TP + FP} \tag{4.3}$$

The model's total accuracy, or F1 score, strikes a positive class balance between recall and precision. Equation (4.4), which represents the calculation, is used.

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4.4}$$

This has to do with how well models (like DNN-LSTM) forecast fish behavior from hydroacoustic data. The capacity of the model to precisely predict fish behaviors and movement patterns is crucial for creating intelligent fish passage systems that work well.

Analyse the degree to which the intelligent fish passage systems can adjust in real time to changes in fish behavior and surrounding circumstances. This entails evaluating how accurately the passages alter their configurations in response to the integrated models' predictions.

Analyse how accurate the overall influence on the restoration of aquatic ecosystems is. Assessing alterations in diversity of species, health of ecosystems, and other pertinent indicators of ecology is part of this. In this case, accuracy refers to how successfully the technologies being used support the recovery of the ecosystem.

Evaluate the precision of data transfer between the smart passageways and the hydroacoustic communication technology. This entails assessing the accuracy and dependability of the communication links used to send information on fish behavior and system modifications. In figure 4.1 shows the evaluation of accuracy.

In the setting of Fish Passage Design and Hydroacoustic Communication, as well as recall relates to the system's capacity to accurately detect and meet the needs of migrating fish. It concerns the percentage of real positive cases (fish passes that are successful or pertinent hydroacoustic signals) that the equipment accurately detects. Regarding Fish Passage Designs, a high recall rate suggests that a considerable proportion of the fish population can move via the structures without any hindrance. Ensuring that the planned target species are accommodated, and their migration is facilitated by the constructed routes is crucial for the successful restoration of aquatic ecosystems.

To summarize, a high recall in hydroacoustic communication means that the system correctly recognizes and interprets relevant underwater signals, which contributes to a greater awareness of fish behavior to enhance passage design and overall aquatic restoration efforts. Conversely, a high recall in fish passage design means that the structures in question are effectively facilitating fish migration. In figure 4.3 shows the evaluation of recall.

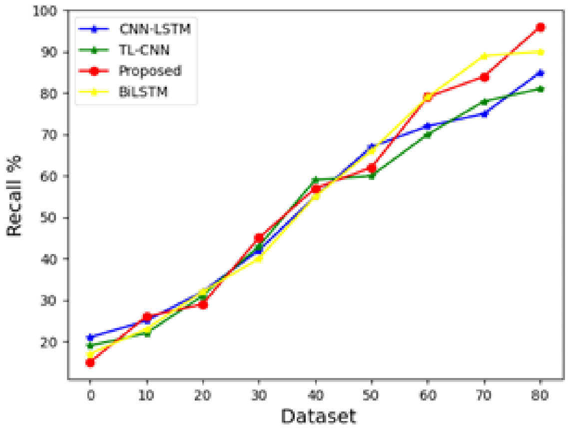

Fig. 4.2: Recall

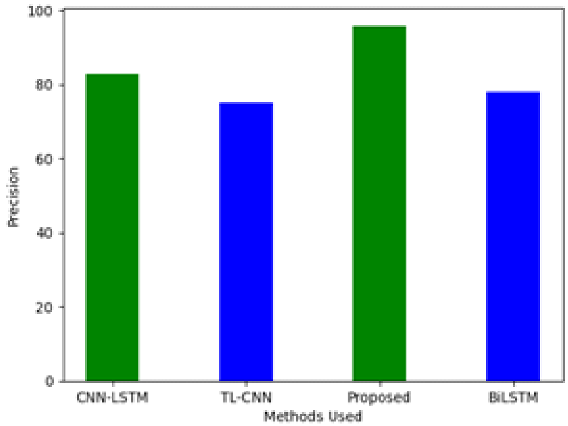

Fig. 4.3: Precision

Recall in Hydroacoustic Communication is the system's capacity to identify and decipher pertinent signals in the submerged acoustic environment. This includes recognizing hydroacoustic cues, such as movement patterns or communication signals, accurately in fish. To collect thorough and precise data on fish behavior—data that can later be utilized to influence the adaptive characteristics of smart fish passages—high recall in hydroacoustic communication is necessary.

When discussing Fish Passage Design and Hydroacoustic Communication, as well as precision pertains to the precision and dependability of the technologies and systems that support fish migration and interaction in aquatic settings. It is imperative to guarantee that the solutions put into practice accurately and successfully tackle the problems related to fish movement and hydroacoustic communications. Fish tunnels must be precisely designed so that the structures can adjust to changing environmental conditions and the unique behaviors of various fish species.

The precise design of the passage structures guarantees the smooth and effective passage of fish, reducing the amount of stress and energy that the aquatic species must expend. Elements that preferentially aid the movement of fish species while discouraging non-target species can be included with precision in design to improve the balance of nature. In figure 4.3 shows the evaluation of precision.

In binary classification problems, the F1-score—also referred to as the F1 measure or F1-value—is a statistic

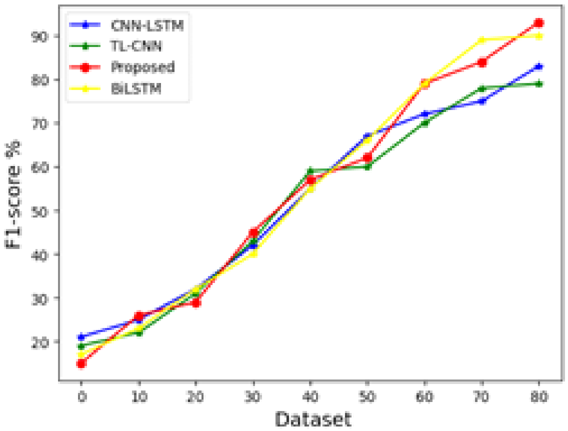

Fig. 4.4: F1-score

that is frequently employed. Recall and precision are used to give a fair assessment of a model's effectiveness. The F1-score could be used to assess how well the system recognizes successful fish passage events in the context of fish route design and hydroacoustic communications. A high F1-score suggests that the algorithm is successfully recognizing effective fish passages while avoiding false positives and false negatives in the setting of fish passage design and hydroacoustic communications. This statistic offers a thorough evaluation of the model's capacity to recognize and react to fish movements inside the intended passageways, accounting for the intricacies of aquatic communications and surroundings. In figure 4.4 shows the evaluation of F1-score.

5. Conclusion. As human pressure on aquatic ecosystems increases and habitat becomes more fragmented, there is an increasing need for innovative solutions to support fish migration and conservation efforts. The focus of this project is to improve rehabilitation efforts for aquatic ecosystems by using smart fish pathway architecture in conjunction with hydroacoustic technologies for communication. The project explores state-of-the-art engineering solutions for fish passage by utilizing complex tracking and regulating systems to enhance migratory paths. Fish populations and monitoring systems can efficiently communicate thanks to the adoption of hydroacoustic technology for communication, which enables real-time data capture and transmission. One main goal of the project is to create intelligent fish passage structures that include actuators, sensors, and communications components. These structures' dynamic response to fish behavior and environmental factors ensures optimal passage efficiency. Hydroacoustic communications technology is a vital interface for behavior data collection, migration trend assessment, and the implementation of adaptive management strategies. A comprehensive field study is part of the recommended methodology to evaluate the effectiveness of the hydroacoustic communication technology and smart fish passage design in a range of aquatic settings. Field data will be examined to assess the impact on fish migration rates of accomplishment, species variety, and overall ecosystem health.The future research directions can contribute to the ongoing development and refinement of hydroacoustic technology for fish migration and monitoring, ultimately advancing the field of aquatic conservation and sustainable management.

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