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AI-Based Fish Fingerling Counting System Using Online Repositories and a Regional Dataset: A Real-Time Monitoring Approach for Aquaculture in Madhya Pradesh

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Abstract: *This research focuses on the creation and utilization of a dataset tailored for the quantification of fish fingerlings in the Madhya Pradesh region, leveraging artificial intelligence (AI) techniques. The dataset encompasses images captured from various water bodies, fish farms, and hatcheries across the region, representing diverse environmental conditions and fish species. Using this dataset, we developed and evaluated an AI-based computational framework employing object detection models such as YOLOv5[1] and Faster R-CNN[2]. The study provides valuable insights into the challenges of fingerling quantification, including occlusion and environmental variability, and highlights the potential of AI in supporting sustainable aquaculture in Madhya Pradesh.*

Key Words: *Fish Fingerlings, CNN, YOLOv5, Aquaculture, R-CNN, Computational Framework.*

1. INTRODUCTION:

1.1 Background and Motivation
Fish farming is a significant contributor to the economy of Madhya Pradesh, with its extensive network of rivers, reservoirs, and aquaculture farms. Accurate fish fingerling quantification is a critical component of effective stock management, directly impacting growth monitoring, feeding strategies, and yield prediction. Manual counting methods remain prevalent but are inefficient, error-prone, and unsuitable for large-scale operations.

1.2 The Role of AI in Aquaculture
AI-based techniques have emerged as transformative tools for precision aquaculture, offering solutions for automated detection, counting, and monitoring of aquatic species. However, the absence of region-specific datasets, particularly for fish fingerlings in the Madhya Pradesh region, limits the applicability of these techniques.

2. LITERATURE REVIEW:

2.1 Fish Fingerling Quantification Methods
Quantifying fish fingerlings is crucial for efficient aquaculture management. Traditional methods of fingerling quantification primarily rely on manual counting, which, while straightforward, has significant limitations. These methods are often time-consuming, prone to human error, and lack scalability, especially in large-scale operations. As a result, manual counting is not an ideal solution for modern aquaculture where high efficiency and accuracy are required.
To address these challenges, image processing approaches have been explored for automated fingerling quantification. Conventional algorithms, such as edge detection and segmentation, have been used to analyse visual data of fish fingerlings. These techniques focus on detecting boundaries and separating individual fish in images, allowing for faster and more accurate counting. However, despite their advantages over manual methods, these algorithms still face challenges in complex environments, such as variable lighting conditions, overlapping fish, and the need for high-resolution imaging.

2.2 AI in Aquaculture

Recent advancements in artificial intelligence (AI) have significantly impacted aquaculture, particularly in the field of fish quantification. Object detection models, such as YOLO (You Only Look Once) and Faster R-CNN (Region Convolution Neural Networks), have shown great promise in accurately identifying and tracking aquatic species. These models can quickly process visual data, providing real-time solutions for monitoring fish populations and behaviour in aquaculture environments. However, the effectiveness of these AI models depends on the availability of high-quality datasets. While there are existing datasets for fish quantification, many of them have limitations, especially when applied to specific regional contexts. Variations in water clarity, fish species, and environmental factors can affect the generalizability of these datasets, making it challenging to deploy these models in diverse aquaculture settings without further adaptation and training.

3. OBJECTIVES:

3.1 Research Gap

There exists a significant research gap in the field of AI-based fish quantification and monitoring in the Madhya Pradesh region, primarily due to the lack of comprehensive datasets that capture the environmental and species diversity unique to this area. The diversity in fish species, aquatic environments, and farming practices across the region poses a challenge for applying generalized models without adjustments. Additionally, there has been limited focus on developing AI-based frameworks specifically tailored to local aquaculture practices. Most existing models are based on generic datasets and methods that do not account for the unique conditions in Madhya Pradesh, such as regional water quality variations, local species behaviors, and traditional farming techniques. This gap presents an opportunity for future research to create more localized, context-specific AI solutions for sustainable aquaculture in the region.

3.2 Research Objectives

This study aims to

- Develop a dataset representative of the fish fingerling population in Madhya Pradesh.
- Propose an AI-based computational framework for automated fingerling quantification.

4. METHODOLOGY:

4.1 Dataset Development

4.1.1. Krishi Vigyan Kendras

The Madhya Pradesh region, known for its abundant natural resources and a thriving aquaculture sector, presents diverse sources for fish farming research and development. Key sites include fish farms, hatcheries, and natural water bodies supported by an extensive network of Krishi Vigyan Kendras (KVKs) distributed across the state. These KVKs, located in districts like Datia, Burhanpur, Katni, and Ujjain, among others, serve as focal points for aquaculture innovation. They integrate research, training, and practical implementation to optimize fish farming practices. Each centre is strategically positioned to harness regional aquatic biodiversity and promote sustainable aquaculture methods. The KVKs, supported by local hatcheries and natural water systems, provide an ideal setting for studies on fish biomass evaluation, behaviour analysis, and water quality prediction, ensuring the development of intelligent aquaculture systems tailored to the specific needs of Madhya Pradesh.

4.1.2. Online Fish Fingerling Repositories [10]

Repository Name	Description	Website Link
FishBase	A global database of fish species, including images of juvenile fish	www.fishbase.org

Aquatic Species Database	Repository of aquatic species with images, including fish fingerlings	www.aquaticspecies.org
Integrated Taxonomic Information System (ITIS)	Provides access to taxonomic information and some images	www.itis.gov
MarineSpecies.org	Database for marine life, including fish fingerlings	www.marinespecies.org
Fish Identification	Offers identification tools and images for various fish species	www.fishid.com
Flickr (Fish Identification)	A community-driven platform with a large number of fish images	www.flickr.com
ImageNet	Large-scale visual database for image recognition research	www.image-net.org
Kaggle Datasets	A collection of datasets for machine learning, including images	www.kaggle.com/datasets
COCO (Common Objects in Context)	Image dataset designed for object detection and segmentation tasks	cocodataset.org
Flickr	A photo-sharing platform with millions of images available under various licenses	www.flickr.com
Open Images Dataset	A large dataset with millions of labeled images for machine learning research	storage.googleapis.com/openimages/web/index.html
Google Open Images	A collection of large-scale labeled	storage.googleapis.com

	images for object detection and classification	
The VisualData Repository	A collection of annotated image datasets for various computer vision tasks	www.visualdata.io
UCI Machine Learning Repository	A collection of datasets for machine learning, including image datasets	archive.ics.uci.edu/ml/index.php
EuroSat	Remote sensing image dataset for land cover classification tasks	github.com/phelber/eurosat
FishBase	A comprehensive database of fish species, including images	www.fishbase.org
DeepFashion	A large-scale clothing dataset with labeled images for fashion tasks	mmlab.ieee.org/projects/deepfashion.html
Pexels	Free stock photo and video repository with high-quality images	www.pexels.com
Unsplash	A platform for free high-resolution photos, suitable for various use cases	www.unsplash.com
Yelp Open Dataset	A dataset with images and business information for recommendation systems	www.yelp.com/dataset
The Oxford Pets Dataset	A collection of pet images for object recognition and classification	www.robots.ox.ac.uk

Table1

4.2.Dataset Characteristics

The dataset for this study is derived from a combination of local aquaculture research sites and global image repositories, each providing unique and valuable insights into fish fingerling quantification. The Krishi Vigyan Kendras (KVKs) scattered across the Madhya Pradesh region are integral to this research. These centres, situated in districts such as Datia, Burhanpur, Katni, and Ujjain, serve as hubs for aquaculture innovation and sustainable practices. They play a crucial role in supporting fish farms, hatcheries, and natural water bodies, offering a diverse range of environmental conditions and fish species. This strategic positioning of KVKs allows for the integration of research, training, and practical implementation, focusing on fish biomass evaluation, behavioural analysis, and water quality prediction tailored to the local ecosystem.

In addition to the local data, several online repositories offer a wealth of information and images that complement the dataset. Repositories such as FishBase, the Aquatic Species Database, and ITIS provide comprehensive taxonomic data and juvenile fish images that serve as essential references for species identification. Platforms like MarineSpecies.org, Fish Identification, and Flickr offer community-driven resources with numerous images of fish species, including fingerlings, which are valuable for machine learning tasks. Further, larger datasets like ImageNet, Kaggle Datasets, and COCO provide labelled images for object detection and segmentation, which are crucial for training AI models for fish quantification. These global datasets, when combined with the local datasets from KVKs, form a robust and diverse collection that captures both environmental and species diversity, making it ideal for developing AI-based solutions for intelligent aquaculture in Madhya Pradesh.

4.3.Computational Framework

4.3.1 Framework Overview

4.3.1.1 Data Acquisition

Data for this study is collected from both local and global sources. Locally, Krishi Vigyan Kendras (KVKs) across Madhya Pradesh, including those in Datia, Burhanpur, Katni, and Ujjain, provide images and data from fish farms, hatcheries, and natural water bodies. These sites offer diverse environmental conditions, essential for studying fish species and behaviour's under varying turbidity, lighting, and fish densities.
Globally, repositories such as FishBase, Aquatic Species Database, and MarineSpecies.org provide images and taxonomic data on juvenile fish. Datasets from platforms like ImageNet, Kaggle, and COCO contribute additional labelled images for training AI models, supporting tasks like object detection and segmentation. This mix of regional and global data forms a comprehensive dataset for fish fingerling quantification.

4.3.1.2 Prototype of Model[11,12,13,14]

The proposed prototype model automates the process of counting fish fingerlings in a transparent water tank using advanced image processing techniques. It integrates both hardware and software components to ensure accuracy and real-time analysis. The hardware setup includes a transparent water tank made from clear material to enable unobstructed visual capture. A high-resolution digital camera is mounted above the tank to capture top-down images of the fingerlings, with adjustable settings for focus, exposure, and lighting to adapt to environmental conditions. Uniform lighting is ensured through strategically positioned LED light sources to reduce shadows and glare. A processing unit, such as a computer or an embedded system like a Raspberry Pi or Jetson Nano, handles image analysis using specialized algorithms.
The software workflow begins with continuous image capture by the camera, followed by pre-processing to enhance the data quality. Noise reduction techniques minimize artefacts caused by water turbulence or reflections on the tank surface, while image enhancement methods like histogram equalization improve the visibility of fish outlines. Data augmentation, including flipping, rotation, and scaling, is applied to the training dataset to improve model robustness. Object detection and counting are performed using deep learning models like YOLO (You Only Look Once) or Mask R-CNN. These models detect individual fingerlings, highlight them with bounding boxes or segmentation masks, and calculate their total count, which is displayed in real-time on a graphical user interface (GUI). The interface also provides visualized data, such as fish positions, and allows users to save the results for further analysis.
Designed to handle real-world variability, the system ensures high accuracy even under different conditions, such as varying fish sizes, movement patterns, and lighting. Its robust pre-processing techniques and deep learning algorithms make it adaptable and reliable. This solution is ideal for aquaculture farms, research facilities, and hatcheries, where it streamlines fish population management, enhances operational efficiency, and reduces manual labour. By combining precision hardware with advanced AI-driven software, the prototype offers a scalable and effective approach to fish fingerlings counting.

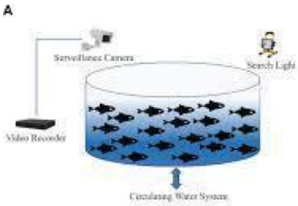

Figure 1: framework model

Figure 2: Sample image (a)

Figure 2.1: Sample image (b)

4.4. Data Pre-processing

In a setup involving a transparent water tank and camera-based image capture, data pre-processing ensures the accuracy and reliability of fish fingerlings detection. Noise reduction is applied to mitigate minor artefacts caused by reflections, minor water turbulence, or lighting variations, using advanced denoising filters. For improved feature visibility, image enhancement techniques such as histogram equalization are employed to optimize contrast and bring out finer details in the images captured through the transparent medium. To further strengthen the model's ability to generalize, data augmentation is performed. This includes operations like rotation, flipping, scaling, and occlusion simulation, replicating diverse perspectives and conditions that might be encountered in practical scenarios. This comprehensive pre-processing pipeline ensures high-quality input data for accurate analysis.

4. 5. Model Training

The model training phase utilizes two selected AI models tailored to the specific requirements of fish fingerling detection. YOLOv5 is chosen for its optimization in real-time detection, making it ideal for fast processing and accurately identifying small objects like fish fingerlings. On the other hand, Faster R-CNN is used for scenarios where high accuracy is paramount, particularly in more complex detection situations where fish may overlap or be obscured. The training strategy involves splitting the dataset into three parts: 70% for training, 20% for validation, and 10% for testing, ensuring robust model evaluation and generalization. *Hyper parameters*, such as learning rates, batch sizes, and anchor boxes, are fine-tuned to align with the specific size and characteristics of the fingerlings. Additionally, transfer learning is applied by utilizing pre-trained models that are further fine-tuned on a regional dataset. This approach enhances the model's ability to extract relevant features, improving its performance in detecting fish fingerlings under various environmental conditions.

5. FINDINGS :

The performance of the fish fingerling counting system is assessed using a range of evaluation metrics. Detection metrics such as Precision, Recall, F1-Score, and Mean Average Precision (mAP) are used to evaluate the accuracy and effectiveness of the model in identifying individual fingerlings. These metrics provide insights into the model’s ability to correctly detect fish, while minimizing false positives and false negatives. Counting accuracy is then measured by comparing the predicted number of fingerlings with the actual counts, offering a quantitative assessment of how well the system performs in real-world scenarios. Additionally, error analysis is conducted with a focus on occluded and overlapping fish clusters, where detection models may struggle to distinguish between closely grouped or partially hidden fish. This detailed analysis helps to identify potential weaknesses in the model and areas for improvement in handling such challenges.

6. DISCUSSION:

6.1 Framework Applications

The proposed fish fingerling counting system has broad applications in various industries, particularly in aquaculture and fish farming. By automating the counting process, the system enhances operational efficiency and accuracy in monitoring fish populations, reducing the need for manual labor and minimizing human error. In aquaculture management, it can be used for real-time monitoring of fish growth, health, and stocking density, providing valuable insights into the management of resources and optimizing feeding practices. The system can also be applied in research facilities focused on marine biology, where accurate data on fish populations is crucial for studying growth patterns, behaviour, and environmental impact. In addition, the wildlife conservation sector can benefit from this technology, enabling non-invasive monitoring of fish populations in natural habitats, which is vital for biodiversity studies and conservation efforts. Furthermore, the food industry can use this technology for quality control, ensuring consistency in fish product sizes for commercial purposes. The framework also has potential in environmental monitoring, where it can aid in assessing the health of aquatic ecosystems by tracking fingerling populations as indicators of environmental changes. Overall, the model provides a versatile, scalable, and efficient solution for a wide range of applications, benefiting both industry and research.

7. CONCLUSION :

The proposed fish fingerling counting system offers a novel and efficient solution to automate the monitoring and management of fish populations in aquaculture and research environments. By leveraging advanced image processing techniques and AI-driven models like YOLOv5 and Faster R-CNN, the system ensures accurate, real-time detection and counting of fish fingerlings, overcoming challenges such as varying environmental conditions, overlapping fish, and dynamic water conditions. The integration of robust pre-processing steps, optimized training strategies, and detailed evaluation metrics ensures the model's reliability and effectiveness in diverse settings.

This system not only enhances operational efficiency in aquaculture by reducing manual labor and minimizing errors but also opens new possibilities in fish population management, environmental monitoring, and research applications. While challenges such as occlusions and environmental variability remain, future improvements in hardware, model robustness, and real-time processing capabilities can further refine its accuracy and scalability. Ultimately, the proposed model represents a significant advancement in fish counting technology, offering a scalable, cost-effective, and adaptable solution for various industries and research fields, with potential for broader applications in sustainable aquaculture and environmental conservation.

8. LIMITATIONS:

The proposed fish fingerling counting model faces several challenges that need to be addressed to ensure its robustness and accuracy in real-world applications. One of the primary challenges is variability in environmental conditions, such as changes in water turbidity, lighting, and reflections on the transparent tank. These factors can significantly affect the quality of the captured images, making it difficult for the model to accurately detect and count the fingerlings. Overlapping and occluded fish present another challenge, as fingerlings often swim closely together or partially hide behind objects, complicating detection and accurate counting. Moreover, the system must be adaptable to different fish sizes and growth stages, as fingerlings vary in appearance as they mature, requiring the model to generalize well across a range of scenarios. Real-time processing is another hurdle, as the system must efficiently handle the data without compromising speed or accuracy, especially in large-scale aquaculture settings where continuous monitoring is essential. Additionally, the quality of the training dataset plays a critical role; collecting diverse and representative data for training can be time-consuming and challenging, especially in regions with limited access to high-quality datasets. Addressing these challenges is crucial for ensuring the model's practical applicability and scalability in aquaculture and research environments.

To enhance the accuracy, efficiency, and applicability of the proposed fish fingerling counting model, several future improvements can be implemented. One of the key areas for improvement is the handling of dynamic environmental factors such as varying water turbidity, lighting conditions, and reflections on the transparent tank. Incorporating adaptive lighting systems and advanced image filtering techniques could help mitigate the impact of these factors. Additionally, improving detection algorithms to better handle overlapping and occluded fish would increase the system's robustness, particularly in environments where fish move in clusters or are partially hidden. This could be achieved by exploring advanced models like 3D convolutional networks or multi-view imaging to better capture the spatial relationships between fingerlings.

Another avenue for improvement is to optimize the real-time processing capability of the system, especially in large-scale aquaculture farms. Implementing faster, more efficient model architectures, such as lightweight versions of deep learning models, could reduce latency and ensure smooth operation in high-throughput environments. Furthermore, expanding the training dataset to include more diverse fish species, varying tank conditions, and different environmental settings would help the model generalize better across a broader range of scenarios.

In terms of user interface, further enhancements could be made to provide more detailed and actionable insights, such as fish health indicators, growth predictions, or automatic alerts for anomalies in fingerling populations. The model could also be integrated with Internet of Things (IoT) devices to monitor other environmental factors in the tank, such as temperature and pH, creating a more holistic monitoring system.

Finally, integrating edge computing capabilities would allow the system to process data locally, reducing dependency on cloud-based services and ensuring faster decision-making in remote or resource-limited environments. By addressing these areas, the proposed model could become even more accurate, scalable, and adaptable for real-world applications, ultimately improving its usefulness in both research and commercial aquaculture.

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