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Automated Pond Identification: Deep Learning with Satellite Imagery for Fish, Shrimp, and Saltpan Ponds

Sudhir Silwal, Anand Tamrakar

M.Tech (AI & ML),Dept. of Computer Science,

Shri Shankaracharya Institute of Professional Management and Technology,Raipur, India

sudhir.silwal@ssipmt.com

Assistant Professor,Dept. of Computer Science

Shri Shankaracharya Institute of Professional Management and Technology,Raipur, India

a.tamrakar@ssipmt.com

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Abstract— Satellites are transforming how we monitor our environment. They provide a vast amount of data that can be used for many purposes. This study introduces a novel work that uses deep learning to analyse satellite images and identify fish farms, shrimp farms, and saltpan ponds. The freely available high resolution Google earth images dataset is used for classifying the pond images. CNN based deep learning models Yolo v7 and YoloV8 explored to train on 20000 labelled images distributed among four classes, we achieved high accuracy in distinguishing between important aquaculture farming practices features. Testing with a large dataset shows that this system is effective and can be used to monitor large areas quickly and reliably. The highest accuracy of 0.93%, precision of 0.91%, recall of 0.70%, and F- Score of 0.90% are achieved using Yolo V8 segmentation model over the pre-processed dataset. This performance highlights the significant promise of deep learning for extracting valuable information from complex, high-resolution remote sensing data. This research is a major step forward in using satellites to manage aquaculture and protect coastal resources, addressing critical challenges in sustainable ecosystem management and conservation.

Keywords— Aquaculture Industry, Deep Learning Models, CNN, Efficient Aquaculture Ponds mapping, Satellite Image

I. INTRODUCTION

Aquaculture, a traditional method of fishery production, has witnessed significant growth since last three decades, particularly in the cultivation of consumable aquatic resources. As per the Food and Agriculture Organization (FAO) statistics, World's aquaculture production surged from 15,000 metric tons to 68.1 million tonnes in the last thirty five years, including 33.1 million tonnes of aquatic animals and 35 million tonnes of algae. India is the third largest fish and shrimp producing country in the world, contributing 8% of global fish production [19][20]. In 2021-22, India produced 16.24 million tonnes of fish, including 4.12 million tonnes of marine fish and 12.12 million tonnes from aquaculture. India is the second largest producer of white leg shrimp in the world. Annually, the production of whiteleg shrimp reaches nearly 1 million metric tons, representing approximately one-sixth of the global production. In 2022, India's shrimp production reached 900,000 tonnes [22][23]. By 2023, Andhra Pradesh emerged as the leading producer of Pacific white leg shrimp in India, with a production exceeding 912,000 metric tons [21][24][25].

Indian aquaculture plays a vital role in enhancing the world's food chain by contributing significantly to seafood production. With a diverse range of aquaculture practices, including shrimp farming, fish cultivation, and brackish water aquaculture, India supplies a substantial portion of the global seafood demand. This sustainable approach not only supports food security but also promotes economic growth and employment opportunities in coastal regions, thereby benefiting both local communities and the broader food chain ecosystem. Along India's coastal regions, aquaculture ponds are integral to the industry, situated in areas rich in biodiversity and ecological significance. These ponds are, either wholly or partly man-made. Aligned with Sustainable Development Goal (SDG) 14 of the "2030 Agenda for Sustainable Development," which emphasizes marine conservation and sustainable ocean resources utilization, the scientific management of aquaculture facilities is crucial for promoting fishery ecology and sustainable development means [22][23][24][25][26].

High resolution Satellite Imagery stands as a highly valuable tool due to its non-invasive and non-disruptive nature, allowing for the simultaneous monitoring of aquaculture ponds with precision across extensive areas and timeframes. This technology facilitates swift and targeted interventions at the farm level, enables regional analyses of ecological shifts over time, supports any administrative level yield predictions for logistical planning, and informs international trade decisions. Accessible worldwide satellite imagery sources further enhance these capabilities, providing a wealth of data freely available to the public. The utilization of satellite imagery in environmental monitoring has significantly advanced our capabilities to study and manage various ecosystems. In particular, the deep learning applications have shown promise in enhancing the analysis of satellite images for diverse purposes. This research focuses on the building and implementation of a deep learning-based approach for the identification of fish habitats, shrimp farms, and salt pan ponds from satellite imagery [3].

Identification of fish, shrimp, and Saltpan ponds through satellite imagery provides a range of benefits to various stakeholders:

- Aqua Farmers: Satellite imagery assists aqua farmers in monitoring pond conditions, such as water quality, pond health, and crop growth. This data helps optimize feed and water management, detect disease outbreaks early, and improve overall farm productivity. It also supports sustainable practices by minimizing environmental impacts.
- Government Agencies: Government agencies benefit from satellite-based pond identification by gaining insights into aquaculture distribution, land use patterns, and coastal resource management. This information aids in policy-making, regulatory enforcement, and monitoring of environmental compliance, ensuring sustainable development of aquaculture sectors.
- Farm Input Providers: Companies supplying inputs like feed, equipment, and technology to aquaculture farms can utilize satellite imagery to target their offerings more effectively. They can tailor products and services based on farm-specific needs, optimize supply chain logistics, and enhance overall efficiency in delivering inputs to aqua farmers.
- Seafood Processors: Seafood processing companies benefit from satellite-based pond identification by ensuring a sustainable and traceable supply chain. They can verify the origin and quality of seafood products, maintain food safety standards, and provide consumers with transparent information about the seafood's source and production practices.
- Seafood Exporters: For seafood exporters, satellite imagery helps in showcasing the traceability and sustainability of seafood products to international markets. It enhances market access, builds trust with consumers, and supports compliance with import regulations and certifications related to sustainable sourcing.
- Salt Manufacturers: Companies involved in salt production benefit from satellite imagery by accurately identifying Saltpan ponds and monitoring salt production activities. It enables them to optimize resource utilization, plan harvesting operations efficiently, and ensure environmental sustainability in salt production processes.

Overall, satellite-based pond identification plays a crucial role in promoting sustainable aquaculture practices, enhancing environmental stewardship, improving productivity and quality in seafood production, and facilitating informed decision-making across the aquaculture value chain [27][28].

The United Nations (UN) and its subsidiary organizations, such as the Food and Agriculture Organization (FAO), have emphasized the importance of sustainable aquaculture management and the conservation of aquatic resources. Satellite-based monitoring plays a crucial role in supporting these efforts by providing comprehensive and real-time data on aquatic ecosystems. In the context of India, a country with a significant coastal area and a prominent fisheries sector, the accurate identification and monitoring of fish, shrimp and saltpan ponds are of utmost importance [21].

This research aims to address these critical aspects by leveraging deep learning algorithms to analyze high-resolution satellite images. By accurately identifying and classifying fish habitats, shrimp farms, and salt pan ponds, this approach facilitates effective monitoring of aquatic environments [16][17][18]. The integration of advanced technology with aquaculture aligns with the broader objectives of promoting sustainability, conservation, and responsible utilization of marine resources [22].

II. RELATED WORK

Previous efforts in aquaculture have primarily focused at the farm level to reduce viral outbreaks. These measures include producing virus-free larvae, implementing management practices such as soil removal and drying, liming, using disinfectants, and biosecurity measures, as well as water management. However, there has been a shift towards utilizing advanced technologies for monitoring and managing aquaculture activities. In this context, the integration of an indicator comprising water, aerator, feeding bridge, and vegetation has been proposed to monitor shrimp pond activity at both hydrological and agricultural scales. This tool utilizes temporal satellite images to depict the history of aquaculture areas over time, providing a broader perspective on aquaculture management [4]. Another methodology proposes a method aimed to validate the hypothesis that water quality parameters, when combined with shape features, play a crucial role in accurately distinguishing aquaculture ponds from other water bodies with similar shapes, such as saltpan, small reservoirs, and rice fields. Through testing conducted at eight coastal sites found that integrating water quality characteristics with six transfer features significantly enhanced the accuracy of differentiating aquaculture ponds from salt pans, rice fields, and wetland areas, achieving F1 scores exceeding 85% [5]. Furthermore, the study introduces a methodology for extracting individual aquaculture ponds from seasonal Sentinel-2 images and merging various sets of pond objects extracted from different images into a unified set of pond objects. The extraction algorithm, originally developed for crop field extraction using Landsat 30 m images, was modified for aquaculture pond extraction using seasonal Sentinel-2 10 m images. Specifically, aquaculture ponds were extracted from near-cloud-free Sentinel-2 images obtained in January and June 2019, coinciding with periods when rice paddies are typically vegetated and to ensure ample cloud-free imagery for comprehensive pond mapping. A multi-temporal object combination strategy was devised to amalgamate ponds extracted at different times into a consolidated set of pond objects. Additionally, the publicly-available Global Surface Water (GSW) product aided in identifying extracted ponds less likely to be aquaculture-related and in excluding a small proportion of rice paddies erroneously included in the extraction results [6].

The study used land use and land cover, specifically the shrimp class, were mapped using DMC3 data for 2019 and Jilin data for 2022, applying unsupervised classification methods. Subsequently, a model accuracy check was conducted using validation data. Spatial analysis techniques applied to generate spatial products at a higher resolution of three meters, effectively capturing and documenting changes over time. The fusion of cutting-edge satellite imagery technology and ground truth data within the system has facilitated thorough and accurate mapping of aquaculture areas. This approach offers valuable insights of coastal pond aquaculture within the region. [7]. An improved U-Net model with a Pyramid Squeeze-and-Excitation (PSE) structure, termed UPS-Net, for the extraction of raft aquaculture areas from high-resolution optical remote sensing images. UPS-Net offers three key advantages: first, the enhanced U-Net effectively captures detailed boundary information and multiscale contextual information of raft aquaculture areas; second, the novel PSE structure adaptively fuses multiscale feature maps, significantly improving performance on the extraction task and reducing the 'adhesion' phenomenon; and third, by incorporating depth wise separable convolution and a pyramid up sampling module, UPS-Net reduces the number of parameters required. Future research should consider the complex environments in which aquaculture rafts are situated, such as the growth stages of seaweed and the status of seaweed harvesting [16][19][20].

III. METHODOLOGY

This methodology involves in this study integrates high-resolution satellite imagery with deep learning algorithms to accurately identify and classify shrimp farms, fish habitats, and salt pan areas. High-resolution imagery enables the detailed capture of aquatic features and their surrounding environments, providing essential data for analysis [19][20].

A. *Study Area*

This paper focuses on the Nellore district of Andhra Pradesh state in India (refer to Fig. 1), renowned as a significant inland shrimp, fish, and saltpan region. It encompasses a diverse marine area, comprising 3,122 hectares of inland and 9,609 hectares of brackish water shrimp resources, totalling 12,731 hectares of aquaculture. This area sustains approximately 40,000 aqua farmers and boasts a coastline of 169 kilometres, supporting 2,909 fishing crafts with a production output of 2.19 lakh metric tons for the year 2023-24. Additionally, salt cultivation spans around 10,000 acres. The primary focus of aquaculture in this region is shrimp farming, which has seen a substantial increase from about 2,000 hectares in 1997 to 12,731 hectares in 2019. In Nellore district, semi-intensive and intensive shrimp farming with varying pond sizes predominates, making the extraction approach's performance applicable to other inland areas [27][28].

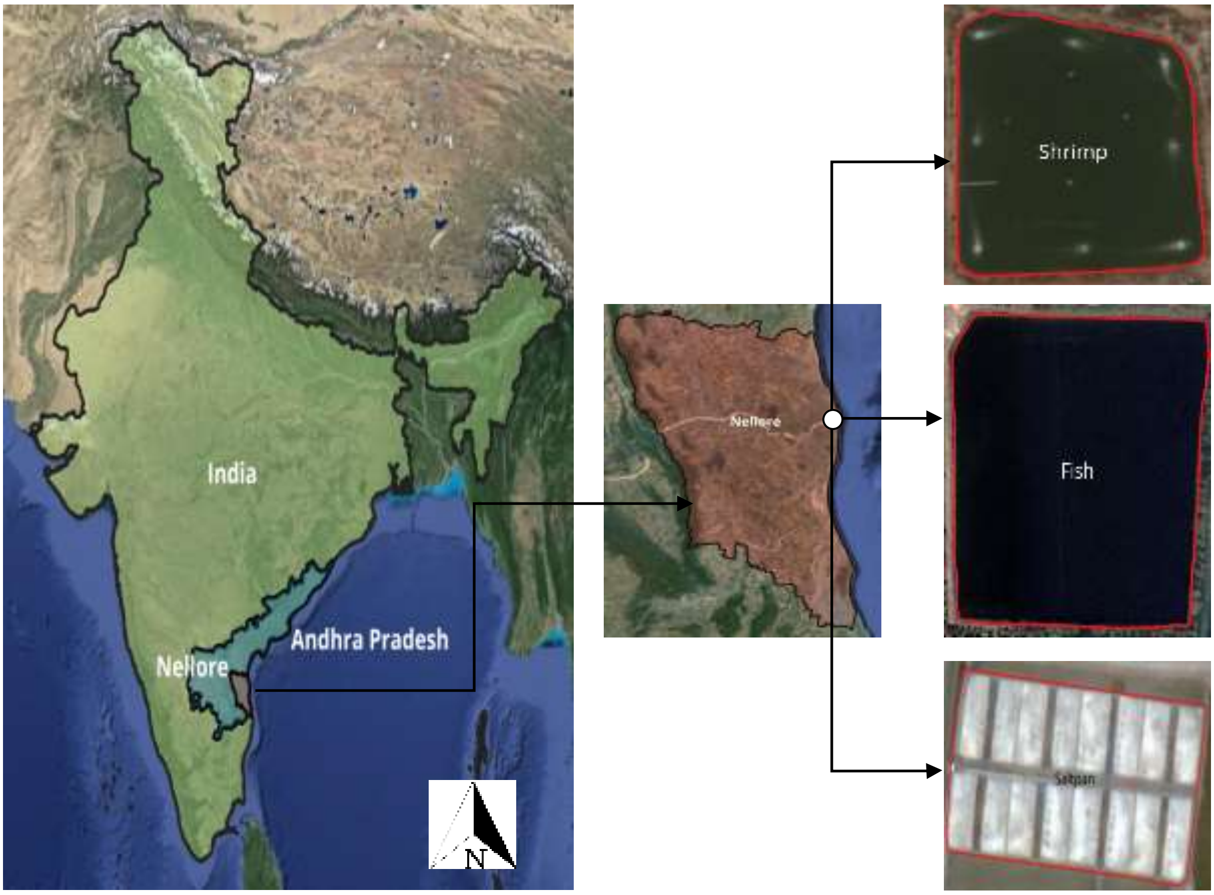


Fig. 1: Study area – Andhra Pradesh State and Nellore District in India

As depicted in Fig. 2, which showcases a 2.4 × 2.9 km area within Nellore subdistricts, This coastal aquaculture system is adjacent to saltpan ponds, featuring expansive ponds constrained by coastlines. These ponds exhibit irregular shapes with high boundary curvature, showcasing the joint operation of salt farming and aquaculture activities in this area. Our survey found that 80–90% of farmers had transitioned their rice fields into shrimp ponds. Most ponds are equipped with aeration system, indicative of semi-intensive and intensive farming practices [1].

Fig. 2: Saltpan and Shrimp farming jointly operated in the Nellore area

In Figure 3(a), the delineated red rectangular shape signifies an individual shrimp farm spanning 1.5 acres and 2 acres, measured precisely using the Google Earth Ruler Tool. Moving to Figure 3(b), the depicted yellow polygon represents the amalgamated Saltpan ponds, each measuring 22 meters in size [1].

Fig. 3(a) Shrimp Ponds in Nellore

Fig. 3 (b) Saltpan Ponds in Nellore

B. *Data Acquisition*

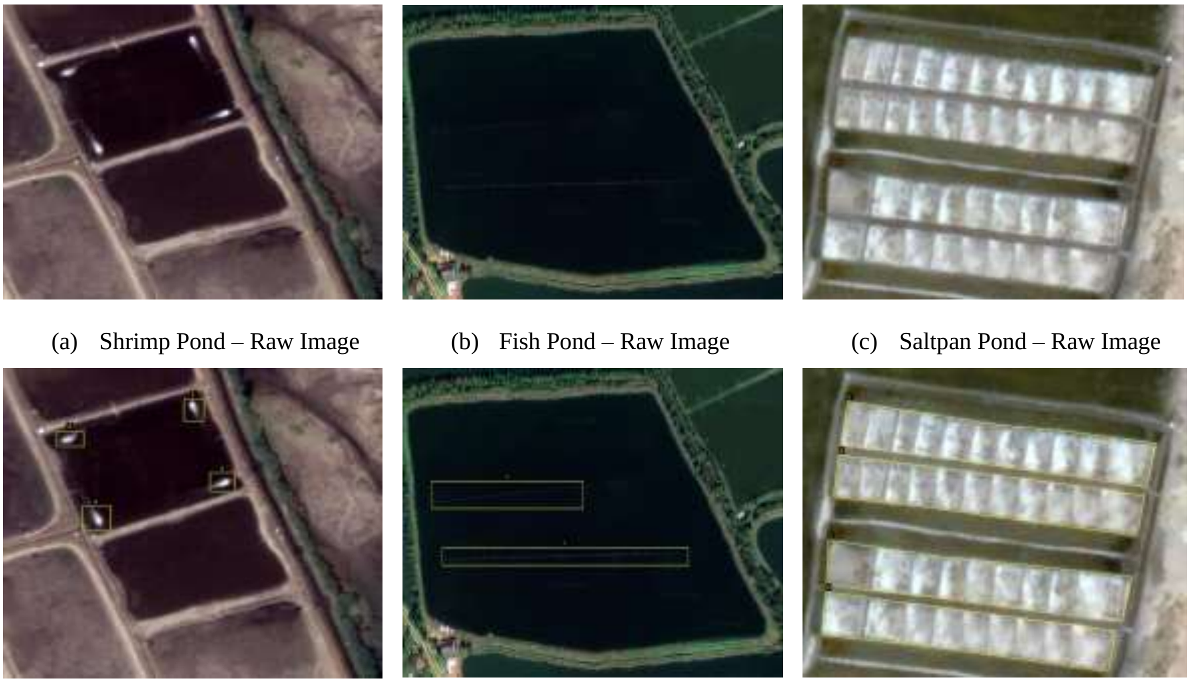
We divided the study area into 100 uniformly-sized rectangular grids, with each grid covering an area of 4 sq. km. This resulted in approximately 1600 images per grid. Due to the Earth's radius decreasing from the equator towards the poles, the height and width of each grid vary with latitude. To address this issue, we maintained constant latitudinal and longitudinal intervals for each grid, ensuring that the spatial resolution remains consistent across the study area. This approach eliminates the curvature effect when stitching images together to generate a comprehensive map of the entire grid for further processing. By establishing these uniform rectangular grids, we ensured a consistent processing unit and maintained spatial uniformity across the study area [1].

To acquire high-resolution images for each grid, a Python-based library, tms2geotiff, which downloads tiles from the Tile Map server, generated a bounding box for every grid, allowing for the efficient downloading of images. The images were obtained consistently in the (xmin, ymax), (xmin, ymin), (xmax, ymax), and (xmax, ymax) directions, with each grid containing approximately 1600 equidistant coordinates corresponding to each image with zoom level 19. We intentionally overlapped images to cover all the complete farm shape in the area [1].

C. *Data Collection*

The Python library was used to retrieve imagery around specific coordinates, with adjacent coordinates chosen to preserve a small overlap between images. The resulting mosaics were cropped and saved as JPEG files. The images were downloaded in TIFF format, which allows for geographical information storage alongside pixel intensities, and stitched together to create a grid box. Unwanted areas of the image were removed, resulting in a high-quality image, cropped to the required size for the algorithm. Ground truth images were manually created using a simple VGG image annotator tool. In our experiment, we tested an image with 640 x 640 pixels resolution for proposed networks. We also used the pre identified pond boundaries including the metadata such as pond centroid and size in this paper [1].

Figure 3 displays raw images (a) to (c) depicting shrimp, fish, and saltpan ponds retrieved from Google Earth, while images (d) to (f) showcase the ground truth data generated using the VGG image annotator tool. The ground truth data was then converted into the YOLO model format to facilitate the training process.



(a) Shrimp Pond – Raw Image (b) Fish Pond – Raw Image (c) Saltpan Pond – Raw Image

(d) Shrimp Pond Ground Truth (e) Fish Pond Ground Truth (f) Saltpan Ground Truth

Fig. 3: Sample Data set Image - Shrimp, Fish, and Saltpan Ponds

D. *Methods*

1) *Yolov7 and YoloV8*

YOLOv7 and YOLOv8 both use a similar backbone network, typically based on a Darknet or CSPDarknet architecture. YOLOv8 is optimized for higher Mean Average Precision (mAP) and lower inference speed compared to YOLOv7. YOLOv8 achieves this by refining the anchorless model with independently structured heads, allowing each branch to focus on specific regression, classification, and detection use cases. YOLOv8, however, introduces enhancements in the CSPLayer (Cross-Stage Partial Layer), now referred to as the C2f module that merges high-level features with related information to enhance model prediction accuracy [9][11].

In YOLOv8's output layer, the sigmoid function works as the activation mechanism for object scores, denoting the probability of an object's existence within its bounding box. Meanwhile, the softmax function denotes class probabilities, signalling the likelihood of an object belonging to a specific class [7][8]. YOLOv8 incorporates Complete Intersection over Union and Distribution focal loss functions for bounding box accuracy, alongside binary cross-entropy for classification precision, thereby augmenting object detection efficacy, particularly for smaller objects [9].

We selected the YOLOv8 architecture based on the expectation that it would offer the greatest likelihood of success for our task. YOLOv8 is considered the new state-of-the-art due to its superior mean Average Precision (mAP) scores and faster inference speed on the COCO dataset, particularly excelling in detecting aerial objects. To implement our approach, we utilized code from the Ultralytics repository. Our strategy involved employing transfer learning by initializing our models with pre-trained weights from a model trained on the COCO dataset before fine-tuning them on our custom dataset [10].

Our paper adopts YOLOv8 as the foundational model, consisting of three crucial elements: the core network, the intermediary network, and the output prediction module. The core network extracts intricate features from RGB colour images, whereas the intermediary network synthesizes and refines these features, including details across various scales [7][8] [9].

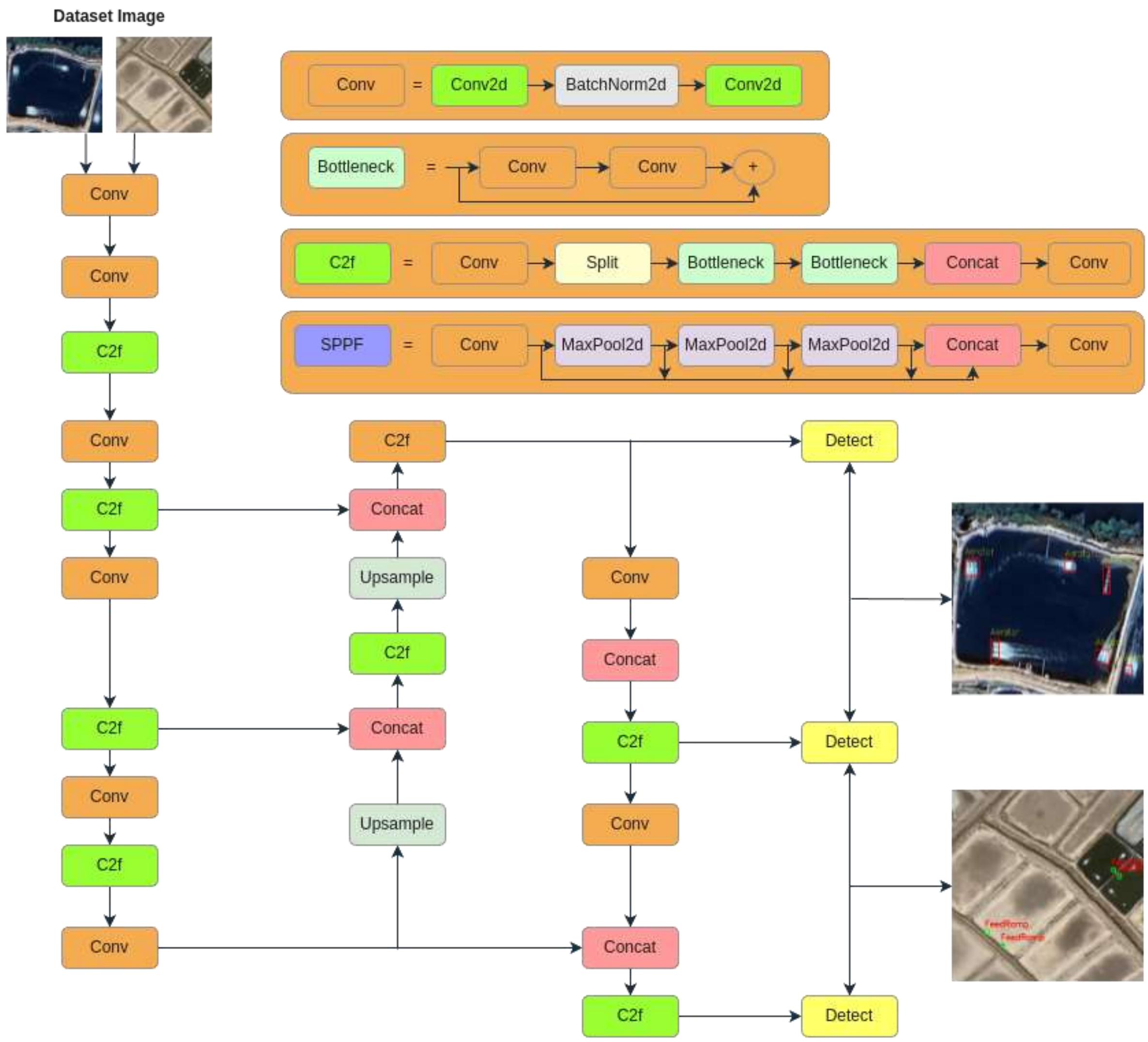


Fig. 4: YoloV8 Architecture

In YOLOv8, the feature fusion mechanism leverages a sophisticated Feature Pyramid Network (FPN) architecture, ensuring an encompassing representation of features.

The prediction output head, positioned atop the model, identifies and locates object categories in images. Multiple detectors within the output head predict object positions and categories, with three sets of detectors operating at different scales to recognize objects from small to large sizes. The model architecture of YOLOv8 is depicted in above Fig. 4. [9][11].

2) *Model Training*

We decided to set the input image dimensions at 640 x 640 is based on achieving a balance between computational efficiency and image detail for detection tasks. This choice ensures that while high-quality images enhance detection accuracy, they also come with a considerable computational burden. Conversely, using low-quality images risks losing important features in each image. Through experimentation, this specific resolution has been determined to yield significant results in previous versions of YOLO [10][15].

We conducted hyperparameter tuning by exploring various parameters to identify the ones that produced optimal results. Two models, YOLOv7 and YOLOv8, underwent training using identical hyperparameters, as detailed in Table 1, to ensure consistency and facilitate fair comparison of results [7][8].

Hyperparameter	**Value**
Epochs	200
Weight Decay	0.0005
LR-Learning Rate	0.01
Batch Size	4
Optimizer	Adam
Momentum	0.912

Table1: Hyperparameters of Training Process

3) Model Process flow

Figure 4 illustrates the pre-processing of the original dataset, followed by its division into training and testing datasets. The best-performing model was then employed to evaluate results using the testing dataset. Geo-coordinates were extracted from the results by overlaying a tif file with the image. Subsequently, all extracted geo-coordinates were inserted into a PostgreSQL GIS database and visualized using the QGIS tool [30].

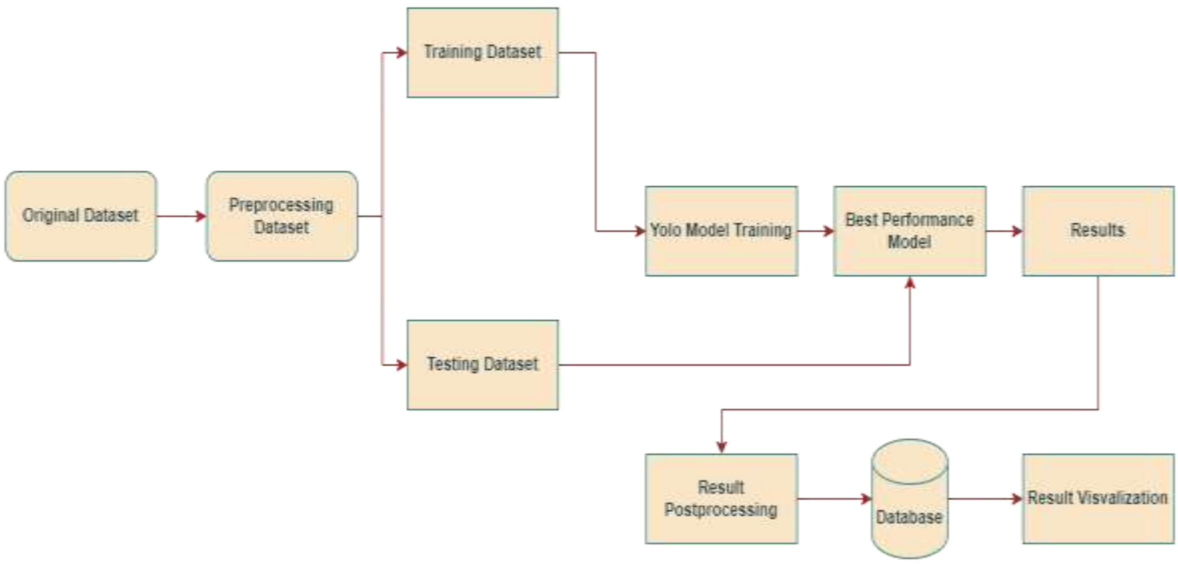


Fig. 5: Process Flow of Pond Detection System

4) Loss function

YOLOv8 adopts the CIoU - Complete Intersection over Union as its primary loss calculation method. Unlike its predecessor DIoU – Distance Intersection over Union, CIoU enhances the loss function by considering the aspect ratio of predicted and actual bounding boxes, making it more attuned to diverse bounding box shapes. However, this improvement comes with increased computational complexity during training [9][11][12].

To address this challenge, WIoU - Weighted Intersection over Union introduces a dynamic focus mechanism, prioritizing dissimilarity over traditional IoU for evaluating anchor box quality. By employing a gradient gain allocation strategy, WIoU mitigates issues arising from competitive high-quality anchor boxes and counteracts adverse gradients from low-quality ones. WIoU comes in three versions: WIoUv1 introduces an attention-based bounding box loss, while WIoUv2 and WIoUv3 further refine the focus mechanism with gradient gain integration, enhancing the overall detector performance [12].

5) System Configuration

Training was carried out on a Ubuntu operating system boasting 32 GB of memory and featuring an NVIDIA Graphics Processing Unit with 12 GB of memory. The YOLOv7 and YOLOv8 model was trained within a Python 3.8 and PyTorch environment.

IV. RESULTS AND DISCUSSION

A. *Experiment*

The multiclass custom dataset comprises high-resolution, fine-grained satellite images for object detection, total of 20,000 images distributed across four distinct classes: aerators, feed ramps, feed lines, and white patch. Figure 8 depicts the class distribution and object sizes within the training set. Notably, the custom dataset exhibits class imbalance, with the "Shrimp" and "feed ramp" classes containing over 16,000 objects each, while the "feed line" and “white patch” class contains fewer than 4,000 objects, as depicted in Figure 6, 7,8, and 9. We divided the images into an 80% training set and a 20% testing set for model evaluation [12[13].

B. *Evaluation metrics*

Assessing the performance of Fish, Shrimp, and Saltpan pond detection models requires reliable metrics that capture crucial aspects of detection accuracy. In this paper, we focus on three fundamental metrics—recall, precision, and average precision to evaluate object detection tasks comprehensively [10][15][29].

Recall, also known as sensitivity or true positive rate, quantifies the ability of a model to detect all relevant objects in a dataset. It is calculated as the ratio of accurately identified targets to the total number of actual targets, expressed as

$$\text{Recall} = (TP/TP+FN) \times 100\%.$$

Higher recall value signifies that the model effectively captures the aerators, feed ramp, feed line, and white patch, but it may also lead to a higher false positive rate [10][15].

Precision reflects the accuracy of a model in correctly identifying relevant objects among all the objects it predicts. It is computed as

$$\text{Precision} = (TP/TP+FP) \times 100\%$$

Here, TP = true positives and FP = false positives. A high precision value indicates that the model produces fewer false positives, ensuring that the detected objects are highly likely to be relevant [10][15][29].

Average Precision (AP) is a comprehensive metric that considers precision at different recall levels, providing a more nuanced evaluation of model performance. It is determined by computing the area under the Precision-Recall (PR) curve, which plots precision against recall. AP reflects the overall detection accuracy across various thresholds and is widely used for benchmarking object detection models [10][15] The formula for AP is

AP = ∫ from 0 to 1 of P(r) dr

Mean Average Precision (mAP) is a composite metric that considers the average precision (AP) values for each class in an object detection task.

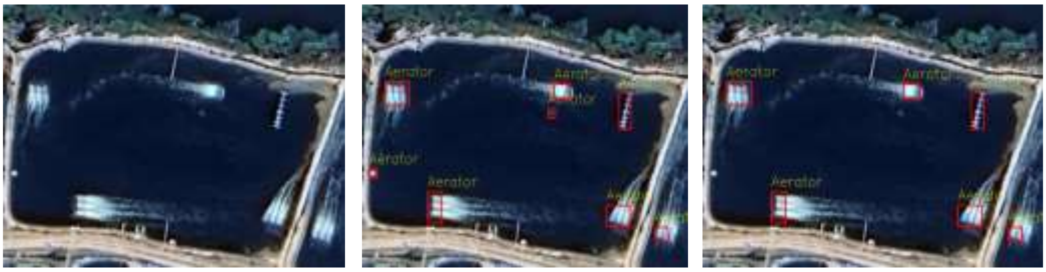
mAP = (Σ from i=1 to n of AP i) / n × 100%

Improving mAP involves enhancing the model's ability to accurately detect objects across different classes while minimizing false positives and false negatives. Strategies such as fine-tuning model architectures, optimizing hyperparameters, and augmenting training data can lead to improved mAP scores [10][15].

C. *Results*

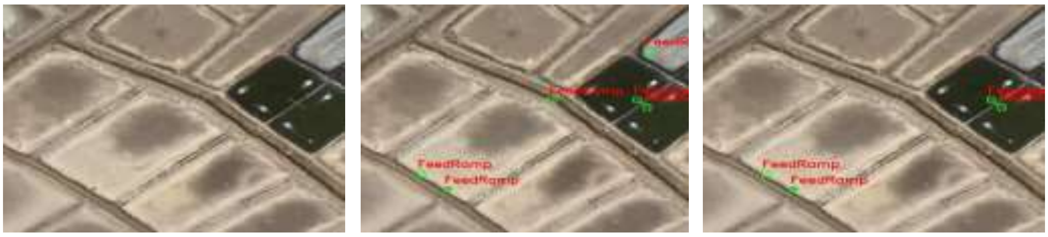
Experiments conducted with YOLOv7 and YOLOv8 on images have produced diverse outcomes, which are demonstrated through examples in Figures 6, 7, 8 and 9. Each figure comprises four sections: the first section displays the input image, the second section presents the results from the YOLOv7 algorithm, and the third section showcases the output generated by the YOLOv8 algorithm.

Fig. 6



(a) Aerator – Raw Image (b) YoloV7 (c) YoloV8

Fig. 7



(a) Feed Ramp–Raw Image (b) YoloV7 (c) YoloV8

Fig. 8

(a) Feed Line– Raw Image (b) YoloV7 (c) YoloV8

Fig. 9

(a) Whitepatch–Raw Image (b) YoloV7 (c) YoloV8

Figure 6(b) highlights the YOLOv7 model's commendable performance in identifying aerators, showcasing its robust capability. However, its misclassification of two other objects as aerators underlines the need for precision in object detection. In contrast, Figure 6(c) unveils the YOLOv8 model's enhanced accuracy, a testament to its advanced algorithm and improved capabilities, crucial for reliable detection tasks. Transitioning to Figure 7(b), the YOLOv7 model's adept detection of feed ramps, including intricate details like the crossing bridge on the canal, underscores its versatility in identifying complex features. Conversely, Figure 7(c) demonstrates the YOLOv8 model's precision, ensuring that only the intended feed ramps are identified, minimizing false detections and optimizing operational efficiency. Figures 6 and 7 reveal the significance of aerators and feed ramp identification in delineating Shrimp farming ponds. In Figures 8(b) and 8(c), both YOLOv7 and YOLOv8 accurately identified the feed line, indicating the pond's use for Fish Culture. Figures 9(b) and 9(c) further depict that both YOLOv7 and YOLOv8 successfully identified the white patch, signifying the presence of a saltpan pond in the area.

Table 2 Algorithm comparison across different YOLO models.

Model	mAP@0.5	Processing Time	Size of the model
Yolov7	0.86	35 ms	24.3 MB
Yolov8	0.92	11 ms	11.7 MB

Table2. Performance metrics of Yolo Models

Table 3 displays the outcomes for each class achieved by the YOLOv8 model. Our model achieved a precision of 0.90, a recall of 0.70, a mAP of 91% at 0.5 Intersection over Union (IoU), and an mAP of 59% at 0.95 IoU. The results obtained from applying the YOLOv8 model to the dataset images are depicted in Figure 8, while Figure 3 showcases the confusion matrix for the trained model.

Class	mAP@0.5	mAP@0.95
Aerator	0.91	0.58
Feed Line	0.86	0.50
Feed Ramp	0.93	0.61
White patch	0.83	0.48

Table3. Class Wise mAP Metrics for Yolov8

V. CONCLUSION

To conclude, this study conducted a thorough assessment of the YOLOv8 object detection model's performance in the crucial task of identifying fish, shrimp, and salt pane ponds. The research provided an in-depth analysis of YOLOv8's architecture and compared it with its predecessor, YOLOv7. An approach to extract individual aquaculture ponds from high resolution images and to combine different sets of pond objects extracted from different images.

The experiments demonstrate the superiority of YOLOv8, as the most efficient and effective model for fish, shrimp, and salt pane ponds detection. It achieved an impressive mean average precision (mAP) of 0.911 at 0.5 Intersection over Union (IoU), alongside maintaining a remarkably low processing time of just 8.8 milliseconds per image. Pond boundaries helped to calculate the size of pond which is the important parameter to distinguish the different types of pond such as fish, shrimp and Salt pane in the study area. Aerators play the important role to identify the shrimp ponds. Large size pond and Feed line is the key indicator to identify the fish ponds. White patch helps to identify the salt pane area. [2][12][13][14][15]

It is recommended for future research to extend this study to include water quality parameters and pond activity monitoring to build robust approach to identify all types of ponds and monitoring changes in pond size over time.

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