技術論文

Do not look so locally to fish skins: Improved YOLOv7 for fish disease detection with Transformers

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Abstract

Aquaculture production significantly influences overall fish production, yet it is often adversely affected by various fish diseases. These diseases can be effectively identified by analyzing the condition of the fish’s skin. Consequently, there is a growing demand for automated fish skin disease detection methods. By implementing such automated approaches, the efficiency and accuracy of disease detection can be enhanced, leading to better management of fish health and, ultimately, more sustainable aquaculture practices. In this work, we propose a novel Transformer based modified YOLO approach for detection of five different fish skin diseases. We propose a Transformer feature extraction module (TFEM) to effectively capture the long-range dependencies from input image. The proposed TFEM is incorporated in the YOLOv7 back- bone for efficient feature learning. We assessed the performance of our proposed TFEM by comparing it with various YOLOvX approaches to confirm its effectiveness. Both qualitative and quantitative results demonstrate that our method is highly capable of accurately detecting five distinct fish diseases. The source code is available at: https://github.com/shrutiphutke/Fish_disease_detection_YOLO_transformer

1 INTRODUCTION

With the world’s population steadily increasing, the demand on traditional food sources is mounting, highlighting the need for sustainable alternatives. Aquaculture emerges as a key solution, offering a dependable source of high-protein food while reducing pressure on marine and terrestrial ecosystems[1]. This not only bolsters food security but also enhances the stability of global food systems. In aquatic food resources, fish food is considered as key resource worldwide in turn becoming the most important factor of the economy. The affected fish due to different diseases causes the limited availability of good quality aquatic food and thus impacts the financial outcomes.

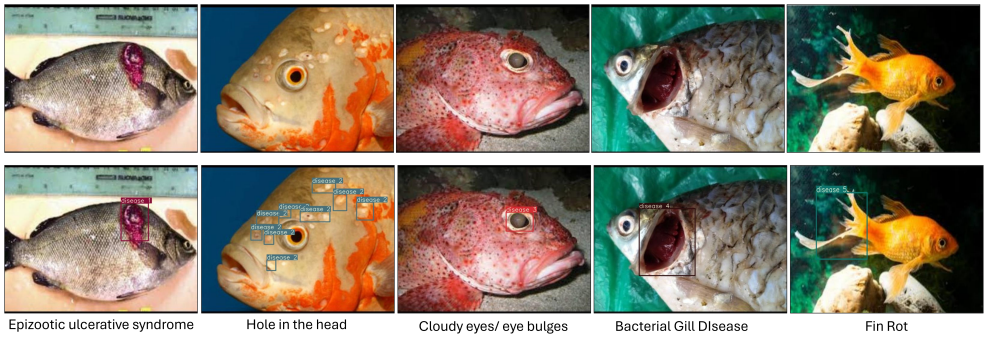

Fig. 1 Sample images of different fish skin diseases

There are various fish diseases caused due to poor water quality, bacterial infection, anchor worms, improper-diet, over-crowding of fish in the tank, etc. The diseased fish generally shows different symptoms such as behavioural or skin color/texture changes. The existing methodology for fish disease detection use expert base system[29], microscopic images[16], fluorescent images[26], ultra sound images[14], body surface images[25], etc. Identifying the type of diseases on the basis of skin abnormalities using body surface images provides the high detection efficiency as compared to disease detection based on the behaviour. In this regard, researchers have proposed different approaches for fish disease detection[11].

In addition to traditional hand-crafted methods, various deep-learning approaches have been proposed for the detection[27][28] and classification[12][4] of fish diseases. These methods encompass a range of techniques, including those that focus on identifying abnormalities in fish behavior and those that analyze skin abnormalities for disease detection and classification. By leveraging deep learning, these approaches aim to enhance the accuracy and efficiency of diagnosing fish diseases, offering more sophisticated and automated solutions compared to conventional methods.

Researchers have primarily focused on the classification of fish diseases rather than on the detection and localization of these diseases[13]. Within this focus, there are numerous approaches developed for identifying various fish diseases[12][4][20]. However, there are relatively few methods dedicated specifically to the localization of diseases[25]. This emphasis on classification highlights the importance of accurately identifying the type of disease affecting fish, while the challenge of pinpointing the exact location of the disease remains less explored.

Existing approaches for detecting fish skin diseases have employed various YOLOvX architectures on fish disease datasets to deliver detection results. These models have been applied directly to the datasets, yielding insights into the presence and extent of skin diseases in fish. In this study, we introduce a modified YOLOv7 approach, distinguishing it from existing methods, with the transformer based backbone foe efficient feature extraction in turn helping for efficient fish disease detection. We considered five different fish skin diseases such as epizootic ulcerative syndrome, holes on the head, cloudy eyes/eye bulges, bacterial gill disease, fin rot, etc. The sample images for each type of disease are shown in Figure 1. The contributions of our work are summarized as:

- We propose a novel modified Yolov7 approach for fish skin disease detection.
- A transformer feature extraction module is proposed in YOLO backbone to extract the efficient features for fish disease detection.
- The extensive quantitative and qualitative comparison is performed to verify the effectiveness of proposed approach for fish disease detection.

2 RELATED WORKS

In this section, we discuss the different approaches proposed for fish skin disease classification and detection.

2-1. Fish Skin Disease Classification

Segmenting fish skin based on texture involves using various clustering techniques to differentiate and categorize different regions of the skin. This process is followed by extracting features from the segmented images, which captures important information about the texture and appearance of the skin. When these extracted features are analyzed using machine learning methods like Support Vector Machines (SVM), it has been shown to enhance the accuracy and effectiveness of fish disease detection[12][4]. This approach leverages the ability of clustering to preprocess and organize data, and the power of SVM to classify and identify potential diseases based on the features extracted from the segmented images. This combination has demonstrated success in improving the detection of fish diseases, providing a robust framework for analyzing and managing fish health. In this regard, Sikder et al.[20] used a Fuzzy C-means approach for clustering followed by Gray level

co-occurrence metrics (GLCM) based features for classifying six different fish skin diseases. A similar GLCM feature based approach is proposed in [2]. Mia et al.[13] used a K-means clustering as a pre-processing step and extracted different features such as mean, standard deviation, etc. to classify the three different fish diseases using various machine learning approaches.

The convolutional neural networks (CNNs), with their end-to-end effective feature extraction ability have been widely utilized for fish disease detection. Gupta et al.[7] proposed a 15 layer CNN approach for wound and lice detection in fish skin. Chen et al.[5] experimented the fish diseased detection using different CNN approaches such as ResNet, DenseNet, etc. Wang et al.[25] analyzed different color spaces of the input image such as RGB, YCbCr, XYZ and proposed a AlexNet and ResNet based approach for classifying three different fish diseases. Further, Azhar et al.[3] used a GoogleNet like architecture to classify the white spot fish disease. A similar, CNN based approach is proposed in [8] to classify white spot, red spot and healthy fish. a fine-tuning based approach is proposed in [15] for fish disease classification.

2-2. Fish Skin Disease Detection

Building on the success of classifying fish diseases using various machine learning and convolutional neural network (CNN)-based approaches, researchers have turned their attention to the localization of fish skin diseases. This shift has led to the development of several new techniques aimed at pinpointing the exact locations of diseases on fish skin. Localization involves not only identifying the presence of a disease but also determining its specific area or region, which is crucial for accurate diagnosis. These emerging approaches combine advanced image analysis and deep learning methods to enhance the precision of disease detection, providing more detailed and actionable insights into the distribution and severity of skin conditions. As a result, these localization techniques represent a significant advancement in the field, improving the management of fish diseases. Yasruddin et al.[27] pioneered the use of Faster Region-based Convolutional Neural Networks (Faster R-CNN) for localizing fish diseases. Yu et al.[28] proposed a Modified YOLOv4 based approach by considering different backbones such as MobileNet, CSPDarkNet, etc. Wang et al.[25] proposed an improved YOLOv5 network consisting of channel and spatial attention mechanism for underwater fish disease detection. Given its effectiveness in capturing global dependencies, researchers have begun applying it to fish disease detection. In [30], authors proposed an improved YOLOv5 based approach by replacing on convolution module in backbone with MobileNetVit (a single transformer block) for fish disease detection based on abnormal behaviour. As seen from the literature, there are very few approaches for fish skin disease detection. Also, considering the existing YOLO based approaches providing sufficient ability for fish skin disease detection, there is a dire need of efficient feature extraction module in the backbone of YOLOv7 for fish skin disease detection. In regards to this, we proposed an efficient transformer based feature extraction module for fish skin disease detection.

3 PROPOSED METHOD

From the existing literature, it is evident that YOLO-based approaches have been employed for fish skin disease detection. However, these methods often utilize the YOLO models directly without accounting for the specific details or characteristics of the input images. As seen from the Figure 1, we can see that different type of skin disease has unique properties such as for Epizootic ulcerative syndrome (EUS) the fish may have wound covering only a smaller region or while body, the hole in head disease has many locations present on the head of fish, etc. The existing approaches may fail at detecting these disease efficiently due to their localized visual ability due to the usage of convolution operation for feature extraction. Also, this oversight may impact the accuracy of disease detection and localization, suggesting a need for more tailored approaches that consider these nuances. Taking into account the ability of transformers to capture global dependencies effectively[23][17], we propose the transformer based feature extraction module in the backbone of YOLOv7[24].

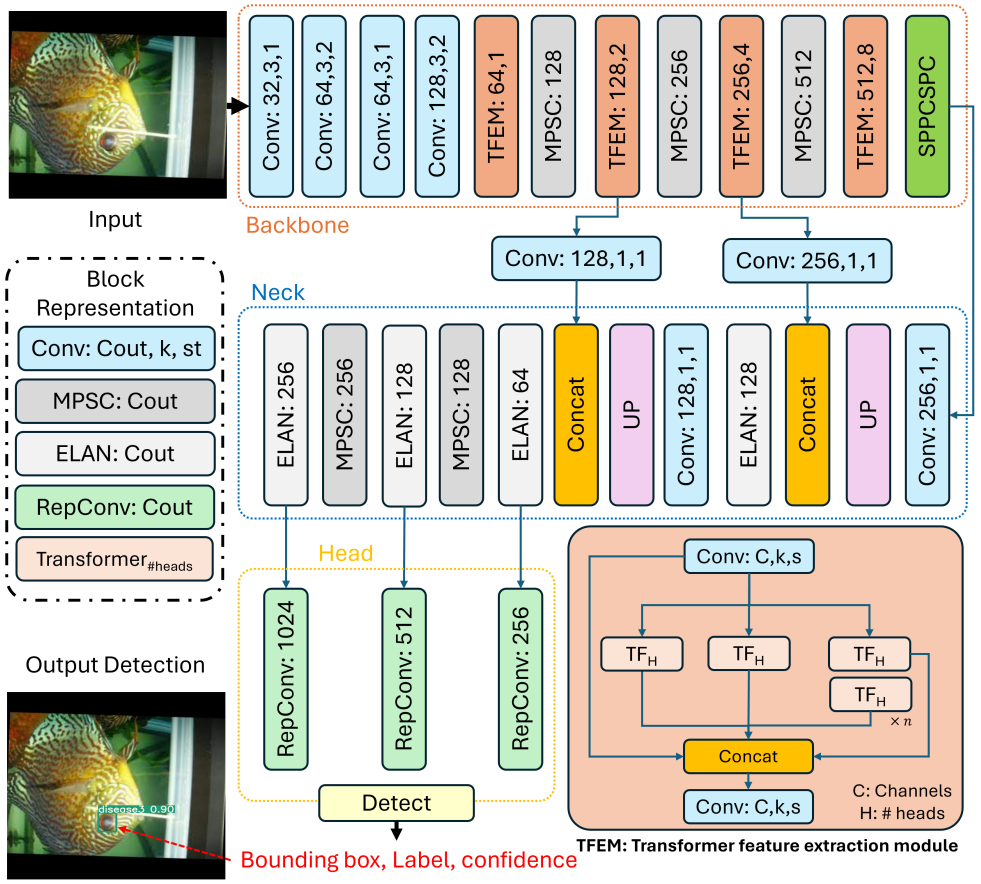

Fig. 2 Proposed architecture for fish disease detection. This is a YOLOv7 based architecture consisting of Backbone, Neck and Head. We propose a Transformer based feature extraction module (TFEM) for efficient feature extraction while capturing long-range dependencies. Further, the architecture consists of different blocks such as: MPSC- Maxpooling-strided convolution, ELAN- Efficient layer aggregation network, UP- upsampling layer, RepConv- Represented convolution, etc.

The proposed YOLOv7 based approach consists of different feature extraction parts such as a backbone, a neck and the head (refer Figure 2). The backbone part mainly contributes in extracting the efficient features from the input image. This plays an important role in capturing the textures, edges, structures, and the complex details from the image. The neck part is mainly responsible to refine and process the features from backbone. With the efficiently extracted features from backbone, the neck part contributed to better detection and localization of diseased region. Further, the head part converts the features into the bounding box co-ordinates, disease class and the confidence score of prediction. By considering the necessity to provide an effective feature extraction module in the backbone, we provided the Transformer feature extraction module (TFEM) in backbone of disease detection network.

3-1. Overview

The input image with size $M \times N \times 3$ is fed as input to the backbone of the network. This image is processed through three consecutive convolution layers to transform it from spatial domain to feature domain. Further, extracted features are down-sampled using max-pooling and stride convolution (MPSC) to a size $\frac{M}{2} \times \frac{N}{2} \times 3C$ and forwarded to the proposed TFEM. The TFEM processes

The features and extract the features by capturing the long-range dependencies with respect to the input. These features are again down-sampled using MPSC to a size $\frac{M}{4} \times \frac{N}{4} \times 2C$. The successive four TFEM blocks with number of heads $H \in (1, 4)$ are used providing the feature map of size $\frac{M}{16} \times \frac{N}{16} \times 5C$ These features are then fed to spatial pyramid pooling cross stage partial connection (SPPCSPC) block which deals with the multi-scale feature processing (refer backbone in Figure 2).

The processed features from the backbone are then fed to neck part of the architecture. The neck part has up-sampling followed by efficient layer aggregation network (ELAN) block. The ELAN block is responsible for efficiently merging the features from the backbone to learn the high-contextual information. The features from last two TFEM module are merged and processed in the neck using the ELAN block producing the feature maps of size $\frac{M}{4}\times\frac{N}{4}\times 2C$. After this, the features are successively down-sampled using MPSC and processed in ELAN block in order to forward them to the detection head. The features of size, $\frac{M}{4}\times\frac{N}{4}\times 2C$, $\frac{M}{8}\times\frac{N}{8}\times 3C$, $\frac{M}{8}\times\frac{N}{8}\times 4C$ are utilized to forward to the detection head.

The detection head consists of represented convolution (RepConv) layers for generating the final detection outcomes in terms of bounding box coordinates, disease labels/type, and confidence score. These predicted bounding box coordinates are then appended on the input to localize the disease predicted by the detection head with respective confidence score (see Output Detection in Figure 2).

3-2. Transformer Feature Extraction Module

The architecture of proposed transformer feature extraction module is shown in Figure 2 (refer TFEM). After processing the features from a convolution layer, they are fed to three different transformer blocks in parallel. Each of the transformer block consists of a multi-head attention followed by a feed forward network. The multi-head attention deals with capturing the long-range dependencies. The process of multi-head attention operation is given as:

$$Attention = \sigma(\frac{QK^T}{\sqrt{d}})V \tag{1}$$

where, σ is Sigmoid activation function, d is a scaling parameter, Q is query, K is key, and

$$Q,K,V = \phi(inputfeatures) \tag{2}$$

where, ϕ is a 3×3 depth-wise separable convolution. Further, the feed forward network in transformer follows a gated attention mechanism as follows:

$$Y_{out} = \phi(inputfeatures)\cdot Gelu(\phi(inputfeatures)) \tag{3}$$

where, $Gelu$ is Gelu activation function. This TFEM process the input features efficiently by the use of stacked Transformer blocks which successively captures more receptive features with respect to the input. The details of the Transformer block, MPSC, SPPCSPC, ELAN, and RepConv are provided in Figure 3.

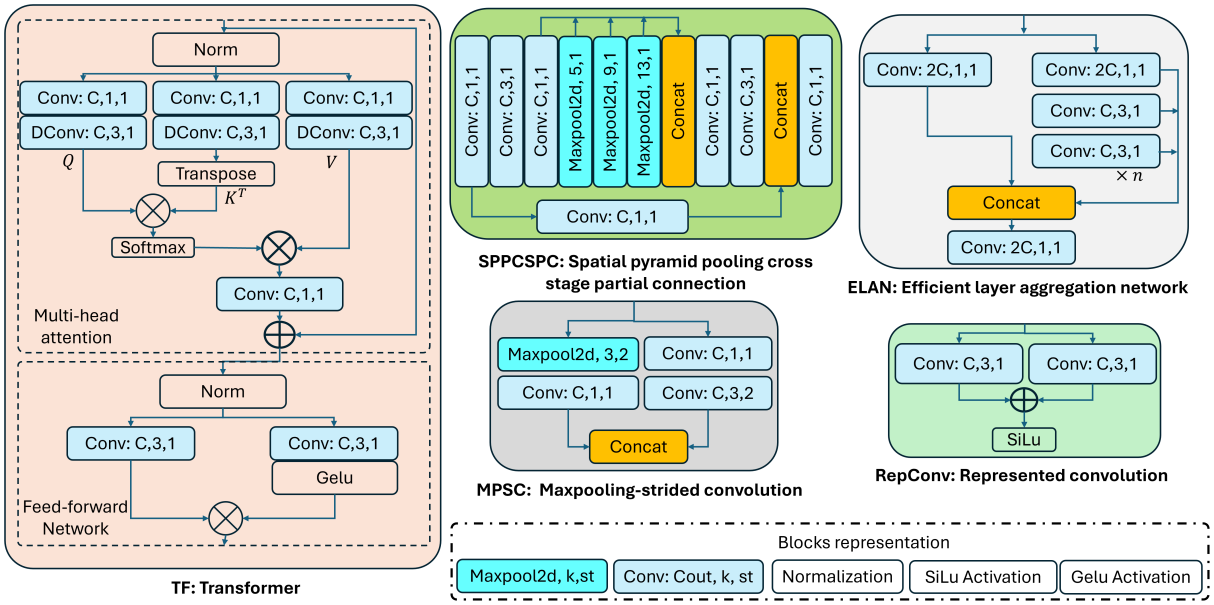

Fig. 3 Details of Transformer (TF), Max-pooling and stride convolution (MPSC), Spatial pyramid pooling cross stage partial connection (SPPCSPC), Efficient layer aggregation network (ELAN), and Represented convolution (RepConv) used in the proposed architecture in Figure 2 for fish skin disease detection

4 EXPERIMENTS AND RESULT DISCUSSION

This section details about the dataset utilized, evaluation measures, training and implementation, results and discussion, and limitations of proposed approach with future scope.

4-1. Dataset

In this work, we utilized a fish disease detection dataset collected from Roboflow. This dataset consists of 4419 images of diseased fishes which are then split into 3858, 381 and 180 for training, validation and testing respectively. The dataset has different augmentations such as horizontal and vertical flip, random rotations, randomly cropping of 0% to 3% of original images, and random shear, etc. This dataset considers five different fish diseases like: Epizootic ulcerative syndrome (EUS), hole/swelling in the head, cloudy eyes or eye bulges, bacterial gill disease and fin rot. The causes of different diseases are described as follows[19]:

Epizootic ulcerative syndrome: are sores that arise from inflammation of the external tissues. They can be caused by a range of factors, including physical injury and bacterial infections. Other contributing factors may include parasites, poor water quality, high ammonia levels, and low pH.

Hole/swelling in the head: The protozoan parasite Hexamita infects the intestines of fish that are already stressed due to overcrowding, poor water quality, or shipping. Parasite infections can advance from the intestines to affect the entire system. When parasites move to the sensory pores on the fish's head, they cause surrounding tissues to deteriorate and result in the development of deep lesions.

Cloudy eyes/eye bulges: It is caused by fluid accumulation behind the eye, but it is frequently the result of an opportunistic bacterial infection triggered by stress or poor tank conditions.

bacterial gill disease is generally caused due to ammonia poisoning in the new fish tank. Can be detected by red or inflamed areas around the gills.

Fin rot disease is generally caused due to poor water quality. This can be detected with the change in color of fins or tail, deterioration of fins and/or tail, frayed edges, inflammation at the base, etc.

4-2. Evaluation Measures

To assess the effectiveness of our proposed approach over existing state-of-the-art approaches,, we employed several evaluation metrics: Recall, Precision, and mean Average Precision (mAP). Recall measures the ability of the approach to identify all relevant instances, Precision assesses the accuracy of the identified instances, and mean Average Precision (mAP) provides a comprehensive evaluation by averaging precision across different recall levels and multiple classes. Using these metrics allows us to thoroughly evaluate the performance and robustness of our method. In a multi-class imbalanced classification problem, precision is computed by dividing the total number of true positives across all classes by the combined total of true positives and false positives for all classes.

Table 1 Quantitative comparison of the proposed work and existing approaches

Method	Recall%	Precision%	mAP50%	mAP50:95%
YOLOv3[18]	90.7	85.9	91.1	69.9
YOLOv5[9]	90.3	**91.7**	92.9	70.3
YOLOv7[24]	92.8	86.6	93.2	70.2
Ours	**94.2**	86.4	**93.4**	**71.4**

$$Precision = \frac{\sum_{c \in C} TruePositives_c}{\sum_{c \in C} (TruePositives_c + FalsePositives_c)} \quad (4)$$

In a multi-class imbalanced classification problem, recall is calculated by dividing the total number of true positives across all classes by the sum of true positives and false negatives for all classes.

$$Recall = \frac{\sum_{c \in C} TruePositives_c}{\sum_{c \in C} (TruePositives_c + FalseNegatives_c)} \quad (5)$$

$$mAP = \frac{1}{C}\sum_{c \in C} AP_c \tag{6}$$

where, AP is average precision, C total number of diseases considered (in this work $C = 5$). The AP is given as:

$$AP = \sum_{k=0}^{th-1} [Recall_k - Recall_{k+1}] \times Precision_k \tag{7}$$

where, th is confidence score (here we considered case 1: $th = 0.5$ and case 2: $th = 0.5 - 0.9$), $Recall_{th} = 0$, $Precision_{th} = 1$.

4-3. Training and Implementation

All the baselines and the proposed approach are trained and tested on the images with 640×640 resolution with *batch size* = 16 for 200 epochs. The networks are trained end-to-end from scratch and the parameters are optimized using Adam optimizer[10] with an initial learning rate of 0.001. A localization loss, confidence loss and classification loss functions are used to train the networks[22]. The Exponential moving average (EMA) approach[21] with a decay of 0.999 is used to train the networks. The training is carried out on NVIDIA A100 GPU. For fair comparison, we trained all the existing approaches and proposed approach with the same training/testing setup and dataset splits.

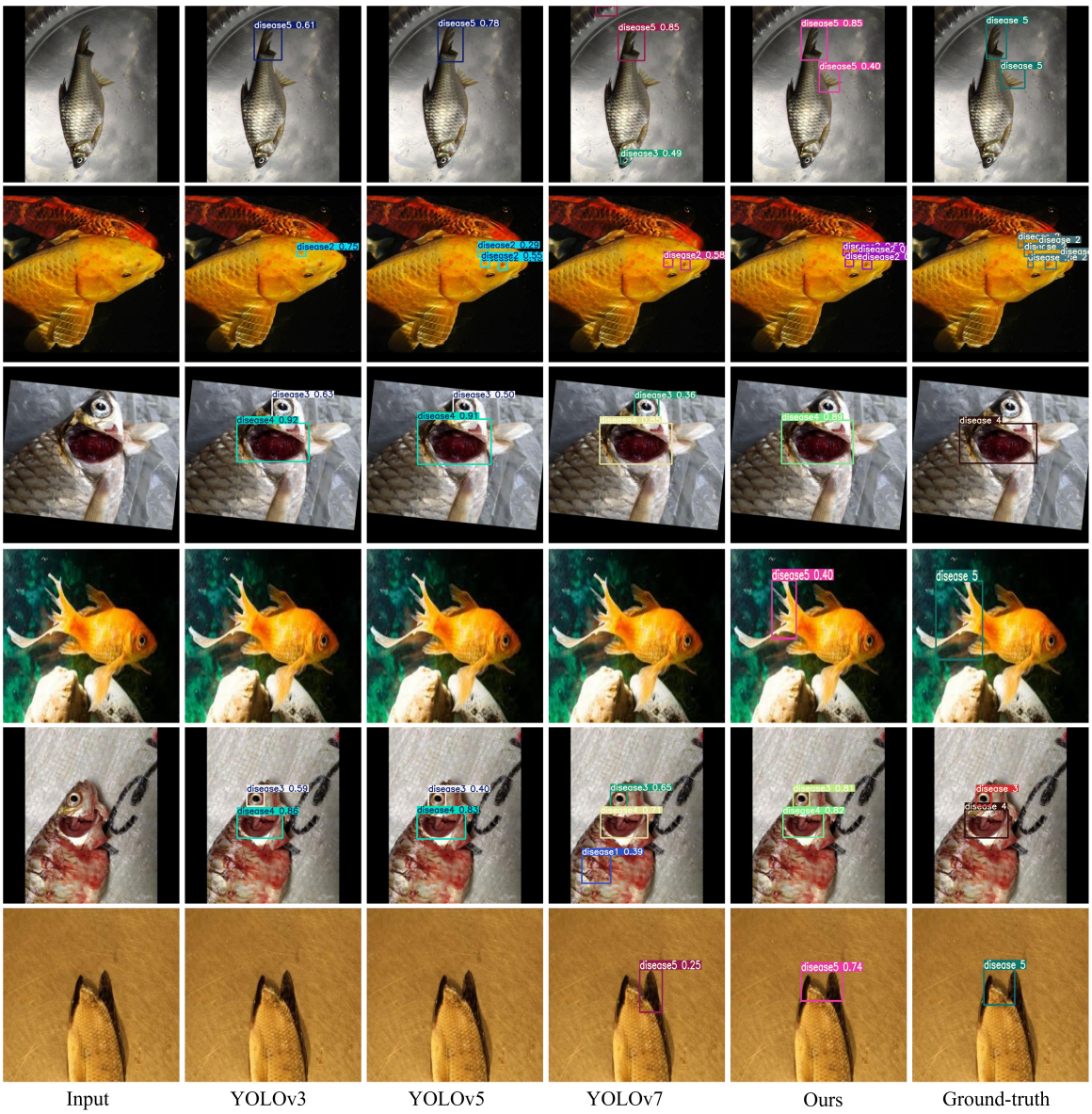

Fig. 4 Qualitative comparison of the proposed method (Ours) with existing state-of- the-art approaches for fish disease detection

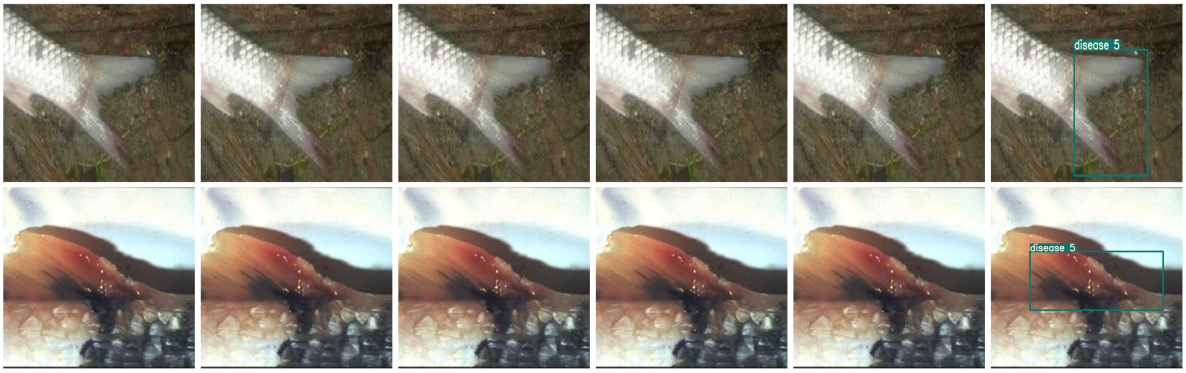

Fig. 5 Limitations of the proposed and existing approaches for fish disease detection

4-4. Results and Discussion

Quantitative Comparison Table 1 shows the comparison of the proposed approach with existing state-of-the-art approaches for detection of fish disease. From this comparison, we can see that the proposed approach proves its efficiency for three evaluation measures out of four considered. The proposed approach has an increment of 1.4% in Recall which shows the ability of proposed approach for correct positive predictions by minimizing the false negatives. Similarly, there is an improvement of 0.2% and 1.1% in *mAP* at 50% and 50%: 90% threshold respectively.

Qualitative Comparison The visual comparison of proposed approach for fish disease detection with existing state-of-the-art approaches is provided in Figure 4. The results shows that the proposed approach is efficient in detecting the correct disease with a high recall (refer row 1,2, and 4 of Figure 4). Also, the proposed approach performs better in minimizing any false positive detection as compared specifically with YOLOv7 (refer row 1,3, and 5 of Figure 4). Further, as seen from the last row of Figure 4, our approach efficiently detects the fish disease with high confidence (0.74) whereas some of existing approaches (YOLOv3, YOLOv5) fail at detection and the other (YOLOv7) has incorrect localization of disease (refer last row of Figure 4).

Limitations and future scope In this section, we discuss the limitations of the proposed and existing approaches for detection of fish diseases. All the approaches considered along with the proposed approach fail at detecting the fish disease in case of camouflage condition (refer row 1 of Figure 5). Further, as shown in row 2 of Figure 5, the detection approaches fail at detecting the fish disease when the image consists of localized part of fish body. In order to overcome these limitations, in future we can extend this work with more efficient feature learning module such as Mamba models[6]. Also, the work will be extended with the efficient performance on different scenarios such as poor lightning, water turbidity, etc.

5 CONCLUSION

In this work, we propose a modified YOLOv7 architecture consisting of transformer feature efficient module (TFEM) in the backbone part for fish disease detection. The proposed TFEM based backbone allows the network to learn long-range dependencies with respect to input image in turn helping the effective disease detection capability. The numeric and visual comparison of the proposed approach is carried out with existing YOLOvX based approaches proving its applicability for fish skin disease detection. Further, the limitations of all the approaches with future scope for reliable fish skin disease detection are discussed.

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