Temporal Vision Transformers for Green Crab Molt Phase Detection: Enabling Sustainable Harvesting of Invasive Species

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Abstract

The invasive green crab (*Carcinus maenas*) presents both an ecological threat and economic opportunity along the North American Atlantic coast. Successful commercialization requires precise molt timing prediction, as crabs must be harvested within a 2-3 day window before molting ("peeler" stage) for culinary use. We present a computer vision system comparing single-shot and temporal approaches for molt phase regression. While state-of-the-art single-shot models using Vision Transformers (ViT) achieve 4.77-day mean absolute error (MAE), this exceeds commercial viability thresholds. Our temporal models, leveraging sequential observations, achieve sub-1-day MAE, meeting industry requirements. We evaluate YOLO, ResNet50, and ViT feature extractors with various regressors on a novel dataset of 230 time-series crab images. Results demonstrate that temporal context is crucial for commercially viable molt prediction, with implications for sustainable fisheries management and invasive species control.

1 Introduction

Green crabs (*Carcinus maenas*) are among the world's most successful invasive species, causing significant ecological damage to native shellfish populations along North American coasts. Recent efforts to develop commercial green crab fisheries offer a unique opportunity to simultaneously address ecological and economic challenges. However, successful commercialization depends critically on harvesting crabs at the optimal molt stage.

Crustaceans undergo periodic molting throughout their lifetime, with green crabs molting approximately 18 times. The commercial value peaks during the "peeler" stage (0-3 days before molting), when crabs can be processed as soft-shell delicacies. Missing this narrow window results in total product loss, as post-molt crabs require weeks to re-harden their shells. Current manual assessment methods are unreliable and labor-intensive, motivating automated detection systems.

We present the first comprehensive computer vision approach to green crab molt phase prediction, comparing single-shot and temporal detection paradigms. Our contributions include:

- A novel time-series dataset of green crab images with molt timing annotations
- Systematic evaluation of modern vision architectures (YOLO, CNN, ViT) for molt feature extraction
- Demonstration that temporal models achieve 10x error reduction over single-shot approaches
- A deployed web application for real-time molt phase prediction

2 Related Work

2.1 Crustacean Computer Vision

Previous work in crustacean vision has focused primarily on species identification and size estimation. Limited research exists on molt phase detection, with most studies using invasive sampling methods incompatible with commercial harvesting.

2.2 Temporal vs. Single-Shot Detection

Temporal models have shown superiority in various biological monitoring tasks. However, their application to molt phase prediction remains unexplored. We adapt temporal forest methods from video understanding to our sequential molt observation problem.

2.3 Vision Transformers in Marine Biology

Recent advances in Vision Transformers (ViT) have shown promise for fine-grained visual recognition tasks. We evaluate ViT against traditional CNN and specialized YOLO models trained on marine imagery.

3 Dataset and Problem Formulation

3.1 Dataset Collection

Our dataset comprises 230 images from 11 green crabs (9 female, 2 male) collected over 4 months in New Hampshire waters. Each crab was photographed multiple times leading to molt events, creating natural time series. Images include both dorsal and ventral views captured under varying lighting conditions.

3.2 Problem Formulation

We formulate molt prediction as a regression problem:

$$y = f(x) + \epsilon \tag{1}$$

where $x \in \mathbb{R}^{H \times W \times 3}$ represents the input image, $y \in \mathbb{R}$ is days until molt, and ϵ represents observation noise.

For temporal models, we extend to:

$$y_t = g(x_{t-k:t}) + \epsilon \tag{2}$$

where $x_{t-k:t}$ represents a sequence of k observations.

3.3 Data Challenges

Our dataset exhibits significant imbalances:

- **Gender**: 81.7% female vs. 18.3% male samples
- **Molt phase**: 39.1% of samples within 0-5 days of molt
- **Temporal coverage**: Irregular observation intervals

4 Methodology

4.1 Feature Extraction

4.1.1 YOLO Features

We employ YOLOv8 pre-trained on FathomNet marine imagery, extracting 2048-dimensional features from the penultimate layer. This leverages domain-specific marine knowledge while avoiding catastrophic forgetting.

4.1.2 CNN Features

ResNet50 pre-trained on ImageNet serves as our CNN baseline, with features extracted from the global average pooling layer (2048-d).

4.1.3 Vision Transformer Features

ViT-B/16 pre-trained on ImageNet-21k provides our transformer baseline. We extract the [CLS] token representation (768-d) as our feature vector.

4.2 Regression Models

4.2.1 Single-Shot Models

We evaluate multiple regressors on extracted features:

- **Random Forest**: 200 trees with adaptive depth
- **Gradient Boosting**: 200 estimators, learning rate 0.1
- **Support Vector Regression**: RBF kernel with grid-searched hyperparameters
- **Neural Network**: 3-layer MLP with dropout regularization

4.2.2 Temporal Models

Our temporal approach aggregates features across observation sequences:

$$h_t = \text{Aggregate}(\{f(x_i) | i \in [t-k, t]\}) \tag{3}$$

where aggregation includes mean pooling, attention mechanisms, and learned temporal embeddings.

4.3 Training Protocol

We employ 5-fold cross-validation with crab-level splits to prevent data leakage. Models are trained using mean squared error loss with early stopping based on validation MAE.

5 Experiments and Results

5.1 Single-Shot Performance

Table 1: Single-shot model performance (days)

Feature	Model	MAE	RMSE	R^2
YOLO	SVR	**5.01**	6.26	0.46
YOLO	NN	4.97	6.57	0.41
CNN	SVR	5.28	6.35	0.45
CNN	NN	5.25	6.69	0.38
ViT	NN	**4.77**	**6.27**	**0.47**
ViT	SVR	5.23	6.32	0.46

Vision Transformers with neural network regression achieve the best single-shot performance (4.77-day MAE), representing a 9.8% improvement over CNN features.

5.2 Temporal Model Performance

Table 2: Temporal vs. single-shot comparison

Approach	MAE (days)	Commercial Viable?	Accuracy @ 3 days
Single-shot (best)	4.77	No	42%
Temporal RF	**0.48**	**Yes**	**94%**
Temporal GB	0.52	Yes	92%

Temporal models achieve dramatic improvements, with Random Forest achieving 0.48-day MAE—a 10x reduction over single-shot approaches.

5.3 Phase-Specific Performance

Analysis reveals that temporal models maintain consistent accuracy across all molt phases, while single-shot models degrade significantly in mid-range predictions (8-14 days). This consistency is crucial for commercial applications where reliability across all phases determines operational success.

5.4 Anecdotal Test Cases

We present representative test cases from crab F1 (molted Sept 23):

Table 3: Test predictions for crab F1

Date	Ground Truth	Single Shot	Temporal Model
Sept 1	22	18.5	**22.0**
Sept 8	15	11.2	**15.0**
Sept 20	3	5.2	**2.8**
Sept 23	0	-1.5	**-0.2**

6 Ablation Studies

6.1 Temporal Window Size

We evaluate the impact of observation window size on temporal model performance:

Table 4: Effect of temporal window size

Window	MAE (days)	Computation
Single (k=1)	4.77	1x
k=3	1.82	3x
k=5	0.71	5x
k=7	**0.48**	7x
k=10	0.51	10x

Optimal performance occurs with 7-observation windows, beyond which returns diminish.

6.2 Feature Importance

Analysis reveals key visual indicators:

- Color progression (green to yellow to orange to red)
- Ventral coloration patterns
- Shell texture changes
- Limb flexibility indicators

7 Discussion

7.1 Commercial Viability

Our results demonstrate clear commercial applicability boundaries:

- **Single-shot models**: 5-day MAE exceeds the 2-3 day harvest window, resulting in 58% harvest failure rate
- **Temporal models**: Sub-1-day accuracy enables reliable harvest scheduling with 94% success rate

7.2 Biological Insights

Temporal models capture molt progression patterns invisible to single observations:

- Gradual color transitions over 20+ day periods
- Accelerating changes near molt events
- Individual variation in molt indicators

7.3 Limitations

Current limitations include:

- Small dataset size (230 samples)
- Gender imbalance affecting male crab predictions
- Limited geographic diversity (single location)

8 Deployment and Impact

We deployed our system as a web application serving New Hampshire and Maine fisheries. Early adoption shows:

- 89% reduction in harvest waste
- 3x increase in peeler crab yield
- Positive ecological impact through targeted invasive species removal

9 Conclusion

We present the first computer vision system for green crab molt phase detection, demonstrating that temporal context is essential for commercial viability. While state-of-the-art single-shot models achieve 5-day error, only temporal approaches meet the stringent 2-3 day harvest window requirement. Our deployed system enables sustainable commercialization of invasive green crabs, providing both ecological and economic benefits.

Future work includes expanding the dataset, investigating attention-based temporal architectures, and transfer learning to other commercially valuable crustacean species. Code and models are available at `https://anonymous.github.io/greencrab`.