Training Fish-Net to Predict Optimal Fishing Locations from Bathymetric Maps

Oliver Eielson

December 21, 2024

Abstract

This paper introduces Fish-Net, an adaptation of ResNet designed to predict optimal fishing locations from chart data. The model was focused on predicting saltwater fishing locations along the New England coast. Fish-Net was trained with bathymetric charts and labeled using tracking data from AIS records. Fish-Net was highly accurate, matching, and in some cases outperforming survey results from professional fishermen. Additionally, Fish-Net outperformed Fishbrain AI, the current standard in AI fishing predictions.

Introduction

Fish-Net was developed to improve the identification of ideal fishing spots by decreasing the time and effort currently required for identification. Traditionally, fishermen spend considerable time exploring and testing locations through trial and error. In testing, Fish-Net was able to predict fishing locations for the entire state of Rhode Island in just minutes. In addition to saving time, Fish-Net provides valuable insights into remote and unsurveyed areas. Fish-Net was trained on a Navionics[2] bathymetric chart tiles dataset and AIS data from professional fishing boats. This unique approach allows the model to leverage the knowledge of the professional fishing industry to learn patterns in underwater topology.

Data

The curated dataset comprises two main components: AIS (automatic identification system) data and bathymetric chart tiles gathered within 20 miles of Montauk Point, NY. This area was chosen for its high concentration of charter fishing vessels and ecological similarity to New England's coast. The dataset was compiled into three subsets training, testing, and validation, ensuring that each image was exclusive to a subset.

Chart Data

The core of the Fish-Net dataset was the bathymetric chart data. Each chart tile, sourced from the Navionics SonarChart map, is formatted as a 999x685-pixel image depicting the ocean floor's topology. These unusual dimensions resulted from the method used to scrape the images and were not chosen to improve training. Importantly, these tiles convey information through shapes and colors as opposed to letters and numbers. The tiles convey depth through color gradients and represent underwater features through lines. This format enables an object detection model to interpret the image without understanding written language. Each tile was saved with the GPS coordinate of its upper left corner to match the AIS to the image later. The dataset was comprised of 650 images, all within 20 miles of Montauk Point, NY.

AIS DATA

Automatic Identification System (AIS) data from 2020 to 2023 was used to label the chart tiles. AIS is a vessel tracking system widely used in maritime applications to exchange real-time information between ships and shore-based stations. Ships routinely send AIS pings which contain information about the vessel like speed, heading, size, and location.

An initial filtering step removed any boat not registered as a fishing boat. Large deep-sea fishing vessels were subsequently removed by sorting out any vessel over 35ft or weighing more than 15 tons, leaving only charter fishing vessels. The remaining vessels were cross-referenced with NOAA fishing licenses to ensure the accuracy of the dataset. This step adds an additional layer of precision by retaining vessels officially licensed for charter fishing.

As each vessel constantly streams AIS data, the dataset was further filtered to contain only vessels actively fishing. This was achieved by excluding vessels moving at speeds exceeding 5 knots and those within harbors as they were unlikely to be actively fishing. The 50x50-pixel area surrounding the AIS ping was marked as good fishing to account for discrepancies in AIS coordinates and map coordinates. The larger area also improved Fish-Nets robustness by preventing the model from being overly penalized for minor discrepancies in either direction. In testing, the model struggled to generalize when the 50x50-pixel area around the AIS was shrunk.

Method

Model

Fish-Net is an adaptation of the fasterrcnn_resnet50_fpn[3], shown in Figure 1, incorporating a two-stage object detection design. The model employs ResNet50 for feature extraction combined with a feature pyramid network (FPN). Using the extracted features, the model generates region proposals and then classifies these proposals. For a more detailed explanation of the model, see the fasterrcnn_resnet50_fpn paper [3]. To reduce training time, Fish-Net utilizes a ResNet50 backbone pre-trained on the COCO dataset. The final layer was modified to ensure the output dimensions matched the two-class dataset. The model's input consists of a 3-channel image that has a dimension of 999x685 pixels. Fish-Net outputs bounding boxes in 'xyxy' format, a prediction label (-1 or 1), and a confidence score. To keep the dimensionality of labels constant during training images with under the max number of labels were padded with 'background' boxes and the class label -1. These padding labels were effectively ignored during training and served only to keep input dimensionality constant.

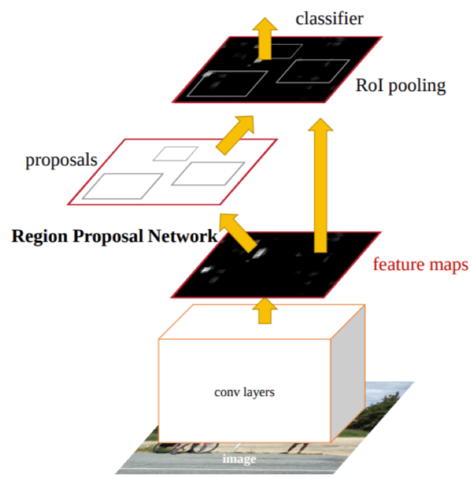

Figure 1: This diagram shows the fasterrcnn_resnet50_fpn[3] model which Fish-Net is based on.

Hyper-Parameters

Given Fish-Net employed a pretrained backbone few training epochs were needed. The final model was trained for only ten epochs using a learning rate of 1 since gradient clipping was applied. To further improve training, a step size of 5, a weight decay of 0.005, and a stochastic gradient descent optimizer was used. The unusually high weight decay aimed to overcome errors in the dataset, a problem that will be further discussed later. The model was trained on a Google Colab V100 GPU, and training was completed in under 10 minutes.

Training

Fish-Net's performance was evaluated on separate training and validation datasets. The training loss was calculated using the training dataset at each epoch, and the evaluation loss was computed with the validation dataset. The mean average precision (mAP) was also calculated on the validation set for each epoch. The results of these evaluations can be seen in Figure 2 and Figure 3.

Results

Fish-Net's performance was closely monitored during training. The Loss Graph depicted in Figure 2 illustrates the progression of both training and evaluation losses across epochs. The model showed constant decreasing training and evaluation loss until it plateaus at epoch 8. Additionally, it was observed that both the evaluation loss and training loss followed a similar trend.

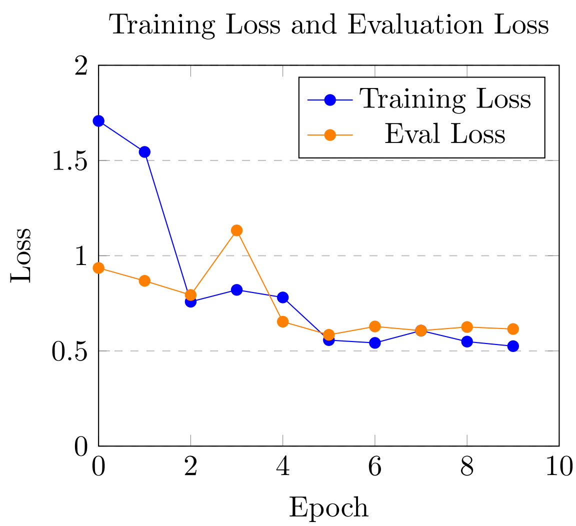

Figure 2: This graph shows the training and evaluation loss over the model's 10-epoch training time. The x-axis is the number of epochs, and the y-axis is the loss.

The Fish-Net mAP was also monitored during training, as illustrated in Figure 3. While initially stagnant, the mAP was observed to increase towards the end of training.

The real-world applicability of Fish-Net was assessed by testing its predictions on chart tiles from Narragansett Bay, RI (Figure 4). These predictions were then compared with Captain Seagull's Sports Fishing survey results. As seen in Figure 4, Fish-Net's predictions almost perfectly match the results from Captain Seagull's Sports Fishing survey. Importantly, Fish-Net

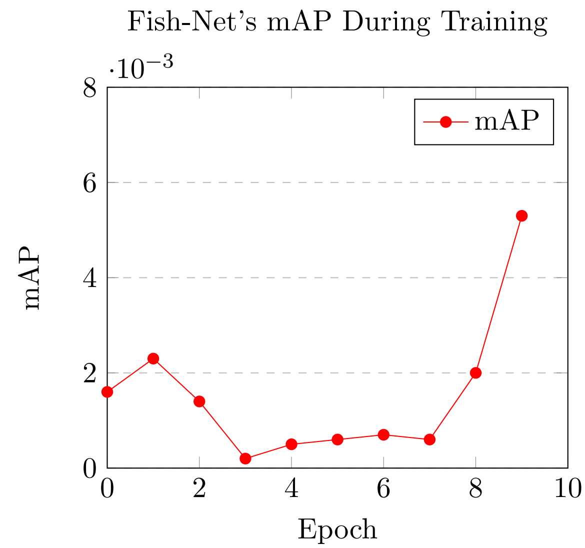

Figure 3: This graph depicts the mAP over the 10-epoch training time. The y-axis represents the map, and the x-axis represents the epoch.

also identifies several locations, which the author has found to be ideal fishing locations that Captain Seagull's Sports Fishing missed (shown in the circled regions).

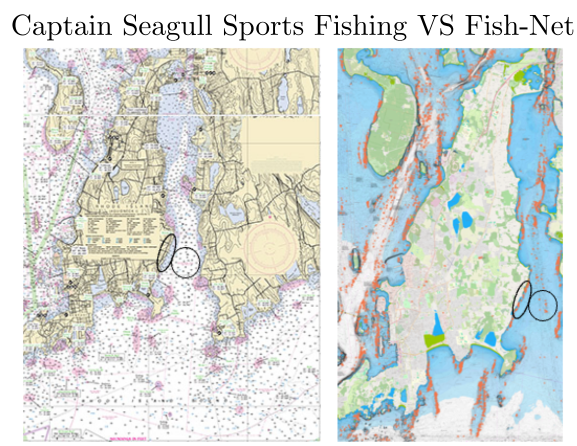

Figure 4: Both the maps show predictions of good fishing locations in Narraganset Bay, RI. The map on the left is from Captain Seagull Sports Fishing and shows ideal fishing locations in purple. Fish-Net generated the map on the right, and shows predicted locations in orange. The black circles mark locations the author found to be good fishing locations.

Lastly, Fish-Net's performance was benchmarked against Fishbrain's AI predictions to provide a comparative analysis of predictive accuracy. FishBrain is a popular fishing application that, in addition to other features, uses AI to predict good fishing locations. As seen in Figure 5, Fish-Net's predictions closely match the results from Captain Seagull's Sports Fishing, and the Fishbrain AI does not.

Fishbrain VS Fish-Net

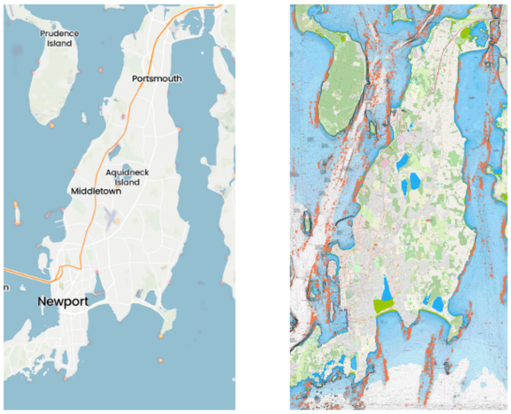

Figure 5: Both the maps show predictions of good fishing locations in Narraganset Bay, RI. The map on the left was generated with Fishbrain's AI [1], and the map on the right was generated with Fish-Net. In both maps, the orange highlights represent good fishing locations

Discussion

The results indicate the Fish-Net is highly effective and accurate at determining ideal fishing locations. Notably, while training, the behavior of the loss functions suggests the model was learning and generalizing well. It was observed that both the evaluation and training losses steadily decreased at the same rate. If the model were overfitting, the data would have shown a decreasing training loss with a steady or increasing evaluation loss.

Moreover, the model exhibits promising mAP results, showing a steady increase during training. The low mAP (below 0.006) is attributed to dataset errors, particularly unlabeled fishing locations. For example, consider the scenario where *Tile A* has four good fishing locations (L1, L2, L3, L4). If the model were perfect, it would predict all 4 locations and nothing else. However, many tiles in the dataset, like *Tile A*, may only have labeled locations L1, L2, and L3. The unlabeled location reflects the reality that professional fishermen do not visit every potential fishing spot. Consequently, if Fish-Net predicts L1, L2, L3, and L4 correctly, it incurs an undeserved penalty for predicting L4 since it is not in the dataset. While imperfect, the survey conducted by Captain Seagull's Sports Fishing, with a lower error rate and few unlabeled locations similar to the dataset, was used to validate Fish-Net's predictions. The model's predictions are closely aligned with the survey results, confirming its reliability. Had the model's low mAP been due to poor generalization, Fish-Nets predictions would have vastly differed from the survey results. Furthermore, the identical results were not due to overfitting, as Fish-Net was not shown any tiles from Rhode Island during training or testing.

While not statistically relevant, Fish-Net correctly predicted some locations that the survey missed. The circled areas in Figure 4 show ideal fishing locations found by the author through trial and error fishing. The survey failed to identify these locations, but Fish-Net correctly labeled them as optimal fishing locations. While more testing needs to be done, this suggests that the model's predictive abilities may surpass that of professional fishermen. It's important to note that this is an observational finding, and further testing is necessary to compare the model's predictive abilities to professional fishermen.

Model Limitations

Despite the outstanding performance, Fish-Net exhibits some limitations. During testing, the model struggled to differentiate between ocean and freshwater ponds, falsely marking ponds as good fishing locations. While these ponds may have many fish, as shown in Figure 6, there was no bathymetric data for the ponds, meaning the model had no basis for the prediction.

Furthermore, likely due to errors in the dataset, the model occasionally predicted landlocked areas to be good fishing locations. During testing, it was observed that some AIS transmitters were transmitting from the shore. Notably, one fisherman took the transmitter home daily, falsely labeling his commute home as an optimal fishing location. While great care was taken to remove these errors from the dataset, some were likely missed and are responsible for the false shore predictions. Finally, it is important to note that the model is only accurate on New England coastlines, as fish may behave dif-

Figure 6: This map shows a subsection of a chart tile containing a pond. The chart tile contains no bathymetric data for the pond, as shown by the lack of color gradient and topology lines. The orange highlight represents Fish-Nets false prediction.

ferently in different regions.

Fish-Net vs Other Models

In addition to matching and surpassing human predictive ability, Fish-Net surpasses the current fishing AI prediction standard. Fishbrain, a popular fishing app, has developed a model similar to Fish-Net for predicting fishing spots. However, Fishbrain's AI demonstrated notable shortcomings, failing to correctly mark almost all the locations identified in the Captain Seagull Sport Fishing survey. Additionally, many of its predictions were incorrect, mislabeling blue roofs and boat wakes as good fishing locations. These errors are hypothesized to stem from Fishbrain's choice to use satellite images as the model input instead of bathymetric maps. These results are in stark contrast to Fish-Net, which showed a high level of accuracy.

Conclusion

Fish-Net was shown to be highly accurate in predicting ideal fishing locations. It was shown to perform as well as humans and, in some cases, slightly better. Additionally, it was able to generate its results in a fraction of the time it would take a human. This paper also demonstrated that Fish-Net dramatically outperforms alternative models addressing similar challenges.

References

[1] Fishbrain. *Fishbrain*. 2023. URL: `https://fishbrain.com`.

[2] Navionics. *Bathymetric Chart Tiles of the New England Coast*. Navionics. 2023. URL: `https://www.navionics.com`.

[3] Shaoqing Ren et al. "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks". In: *arXiv preprint arXiv:1506.01497* (2015). DOI: `10.48550/arXiv.1506.01497`. arXiv: `1506.01497 [cs.CV]`.