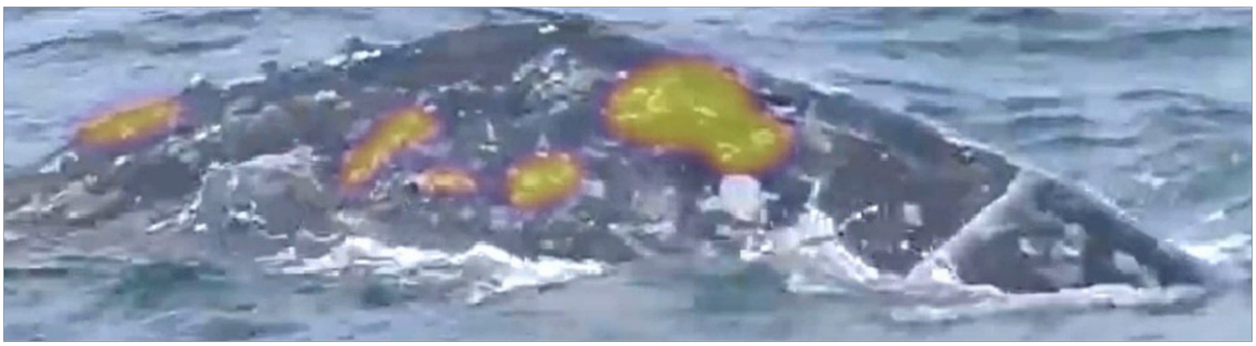
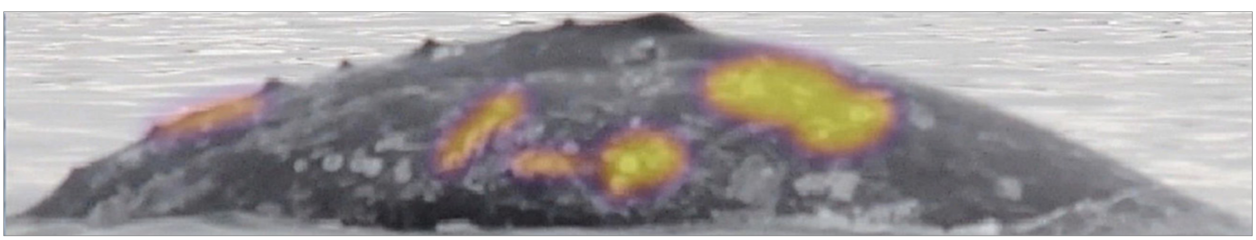
OCS Study
BOEM 2021-059

Feasibility Analysis: Using Artificial Intelligence to Match Photographed Lateral Ridges of Gray Whales





U.S. Department of the Interior
Bureau of Ocean Energy Management
Pacific OCS Region

BOEM
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BOEM 2021-059

Feasibility Analysis: Using Artificial Intelligence to Match Photographed Lateral Ridges of Gray Whales

August 2021

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Prepared under Contract 140M0120P0023
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Bureau of Ocean Energy Management
Pacific OCS Region

DISCLAIMER

Study concept, oversight, and funding were provided by the U.S. Department of the Interior, Bureau of Ocean Energy Management (BOEM), Pacific OCS Region, Camarillo, CA, under Contract Number 140M0120P0023. This report has been technically reviewed by BOEM, and it has been approved for publication. The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the opinions or policies of BOEM, nor does mention of trade names or commercial products constitute endorsement or recommendation for use.

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CITATION

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ABOUT THE COVER

Cover photos display example visualizations of corresponding texture patterns in lateral photographs of a previously matched gray whale resighted several years later.

ACKNOWLEDGMENTS

This report acknowledges additional support from the National Oceanic and Atmospheric Administration's National Marine Fisheries Service, Southwest Fisheries Science Center under Contract Number 1305M320PNFFR0479.

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List of Abbreviations and Acronyms

AI	Artificial intelligence
BOEM	Bureau of Ocean Energy Management
ML	Machine learning
PIE	Pose Invariant Embeddings

1 Executive Summary

Wild Me (wildme.org) completed all tasks for BOEM Award 140M0120P0023 and NOAA Award 1305M320PNFFR0479 (collectively the "AI for Gray Whales" project) and is submitting this final report to complete the project. Wild Me evaluated four distinct computer vision approaches to reliably reidentify gray whales (*Eschrichtius robustus*) from lateral photos.

Among the evaluated techniques, the HotSpotter and PIE algorithms provided the most overall matching power with an additive performance of top-1 rank of 70% and top-12 of 92%, depending on their chosen configuration and the selection of test data. All developed and tested machine learning models and ID algorithms evaluated under these awards are now available in Flukebook.org for evaluation and use.

1.1 Completed Task Summary Table

The following tasks were completed under both awards, summarized as "NOAA" (1305M320PNFFR0479) and "BOEM" (140M0120P0023).

Table 1. Completed Tasks Summary

Task	Computer Vision Techniques	Status	Award
Import 2000-3000 NOAA-provided gray whale photos for annotation and labeling in the IBEIS interface. Diversity in data is most important here.		**COMPLETE:** Wild Me imported over 2100 of the most diverse photos available (from multiple contributors, multiple lighting and sea state conditions, etc.) of gray whale lateral photos.	NOAA
Annotation lateral photos of gray whales for bounding box and viewpoint		**COMPLETE:** Wild Me drew bounding boxes around imported photos. Example video used for annotation: https://youtu.be/rS5lmQKjceE 2085 images were annotated from across the data sets provided. 2182 annotations (bounding boxes) were made, representing some photos with >1 whale.	NOAA

Task	Computer Vision Techniques	Status	Award
Detection model training	Deep Learning [A, B]	**COMPLETE:** Wild Me created a deep learning model that allowed future photos to be curated without human intervention (finding the animal in the image, removing background pixels, predicting viewpoint). This model is the precursor to second-stage individual ID with algorithms and machine learning. Examples of detector output have been zipped up here: https://drive.google.com/file/d/18ElLvknV3v79JcxxffAz8y7En1bUP7zJ/view?usp=sharing Detector model performance results are summarized below in the "AI for Gray Whales Q4 Progress Report".	NOAA
Data blending of legacy data, linking at least photos to IDs		**COMPLETE:** Wild Me blended legacy data sets for gray whales into the Wildbook standard import format.	NOAA
Import blended data into Flukebook.org		**COMPLETE:** Blended historical data was imported into Flukebook.org where it is secured for private access and wherein matching algorithms can be run.	NOAA
Run detection machine learning model on imported Flukebook data, creating annotations with associated IDs for matching comparison	Deep Learning [A]	**COMPLETE:** The machine learning model created above was run on the historical data to create "Annotations", which denote animals in images with labeled viewpoints and assigned IDs. Annotations are the units of matching in Wildbook and Flukebook. In conjunction with Cascadia Research Collective, Wild Me also completed an ID review, ensuring that all annotations assigned to an ID belonged to that ID, ensuring a high quality training data set. The resulting spreadsheet can be found here: https://docs.google.com/spreadsheets/d/1eS_ACzY-4BrEOp8KGp6lV_CCjrj6Rr08bdURL9NulZQ/edit?usp=sharing	NOAA

Task	Computer Vision Techniques	Status	Award
Evaluate the HotSpotter algorithm performance on matching lateral gray whales (e.g., top-1 % correct match, top-5%, etc.). Generated require reports and project summaries.	HotSpotter [C]	**COMPLETE:** Annotations were compared to determine the % accuracy when used to compare the same individuals' photos against a catalog of other individuals.	BOEM
Evaluate finFindR or CurvRank algorithm performance on matching lateral gray whales (e.g., top-1 % correct match, top-5%, etc.). The algorithm chosen for full evaluation will be decided after a literature and functional review.	CurvRank v2 [E]	**COMPLETE:** CurvRank v2 was chosen after demonstrating its superior performance over the current generation of finFindR for multiple species in the "AI for MAPS" BOEM project. CurvRank v2 was retrained on over 2000 hand-traced dorsal ridges to ensure maximum performance for the gray whale use case. With the gray whale CurvRank v2 model created, annotations were compared to determine the % accuracy when used to compare the same individuals' photos against a catalog of other individuals.	NOAA
Retrain and evaluate right whale lateral matching performance developed in NOAA contract 1333MF19PNFFM0139 on matching lateral gray whales (e.g., top-1 % correct match, top-5%, etc.)	PIE [D]	**COMPLETE:** Annotations were compared to determine the % accuracy when used to compare the same individuals' photos against a catalog of other individuals.	NOAA
Generate a final report of matching performance for NOAA and suggest avenues forward.		**COMPLETE:** Wild Me staff collaborated to generate this summary report of all work and its outcomes.	NOAA

1.2 CurvRank v2, PIE, and Combined Performance Results

1.2.1 Adding CurvRank v2

From April to May 2021, Wild Me Machine Learning Engineer Drew Blount re-trained CurvRank v2 [5]. Prior to this retraining, Wild Me's annotation team completed the precursor dorsal ridge tracing of 2182 annotations that were used in the training. A zip file of the visualizations of the tracings for that can be found here:
https://drive.google.com/file/d/1scJUhkTthQl964R1c0JHNBO31obbdmUl/view?usp=sharing

We performed a number of training experiments, including different techniques for mirroring right-side images to have a left-like appearance, and exploring the parameter space of the CurvRank v2 training pipeline by modifying the learning rate, training time, or image resolution. We also tried swapping out components of the gray whale model with components from a CurvRank v2 model trained on dolphin and baleen whale dorsal fins: CurvRank v2 has three distinct models which operate in series, and we tried various combinations of those trained on gray whales, and those trained on dorsal fins. Our most accurate model did not use any of these dolphin-trained components.

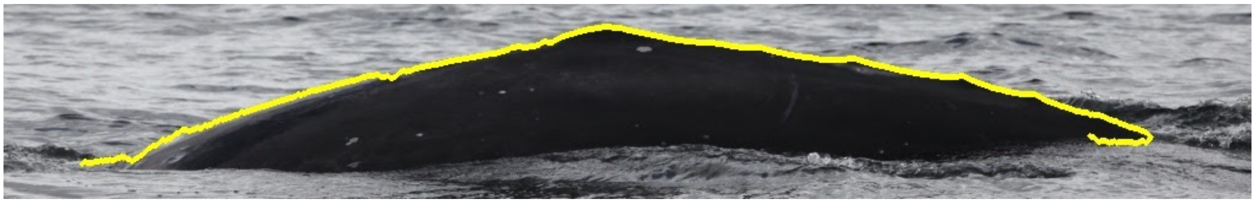


Figure 1. An automatically-extracted curve from our gray whale model. The errors on the ends are consistent with CurvRank's behavior on dolphin dorsal fins, where matching is significantly more accurate.

Despite showing a consistent ability to extract the edges of gray whale dorsal ridges, though with some errors (pictured above), CurvRank v2 was not very effective at matching these edges, with a top-1 accuracy of 20%, rising to a top-20 accuracy still shy of 50% --- in fact, 43.5% on our test dataset with a minimum of 2 sightings per individual, charted below. We are not certain why accuracy is so low, but a large variety of experiments we performed with CurvRank v2 and this data produced similar results, so we believe it may simply be a poor fit by the algorithm when computing the visual features.

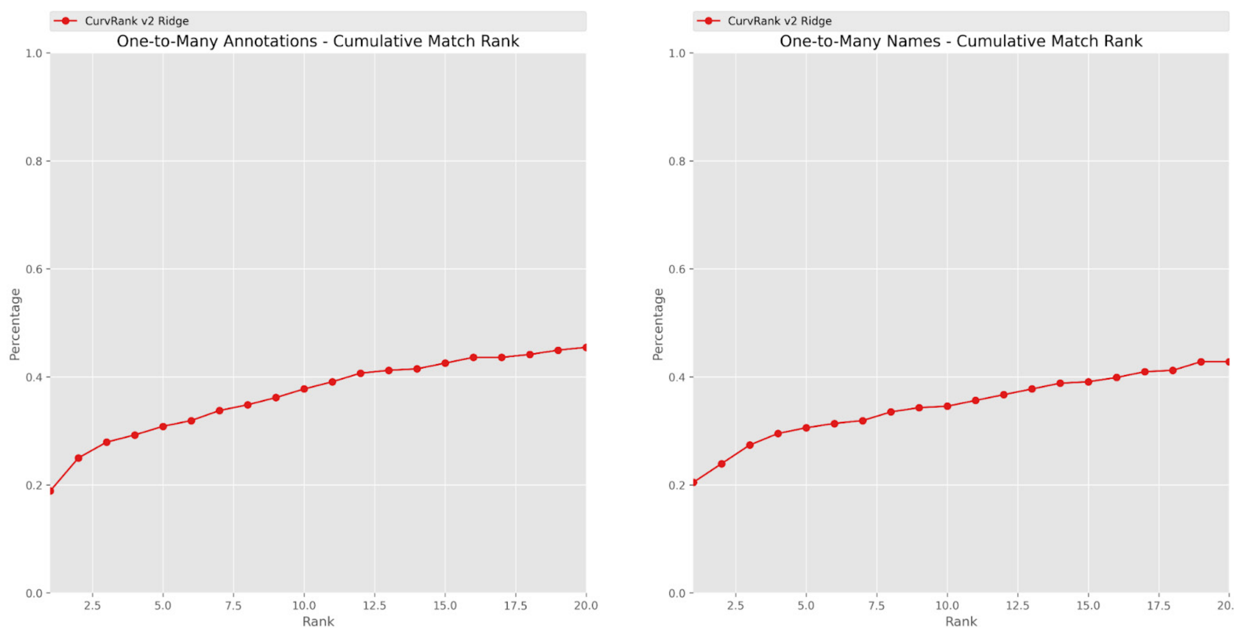


Figure 2. CurvRank v2 top-N ID matching performance

1.2.2 Evaluating PIE v2

During the course of this project, PIE's original developer Olga Moskvyak developed a second generation of the algorithm in the context of a separate project with Wild Me to modernize whale shark (*Rhincodon typus*) photo ID on whaleshark.org. PIE v2 significantly outperformed PIE v1 in that context and provided a more maintainable technical foundation with a switch from TensorFlow to PyTorch at its core (i.e. PIE v2 requires less computational resources and runs a more stable codebase), and we chose to go above and beyond our contracted obligation and also evaluate PIE v2 on gray whale flanks. Olga reported an independent performance of the following for gray whales with PIE v2 (training on the right sides and testing on the left with min 3 images per name):

- Top-1 : 69.0%
- Top-5 : 81.4%
- Top-12 : 86.7%

We evaluated PIE v2 independently and achieved the following comparative plot. Note that this plot assumes a minimum of three annotations (min-3) of a side per individual.

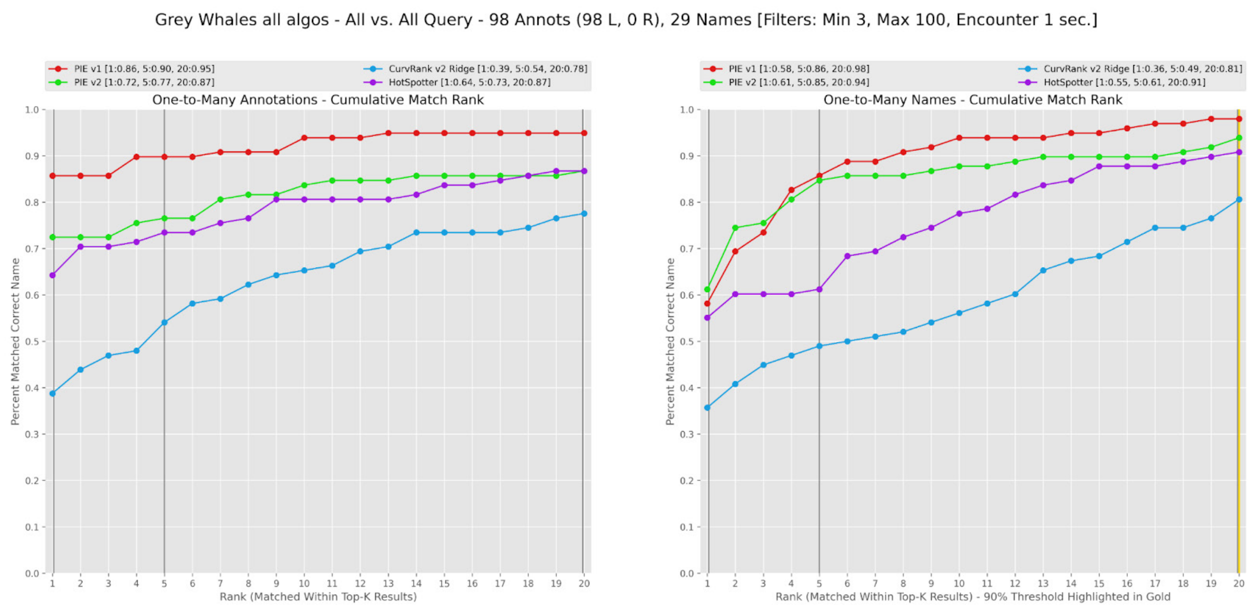


Figure 3. Combined top-N accuracy for all evaluated ID algorithms

Our review showed slightly lower Top-1 performance for PIE v2 but higher top-5 and top-12 performance than reported by Moskvyak. This discrepancy is explained by differing test setups and slight changes in experimental environments between Moskvyak and Wild Me. An interesting caveat of our reanalysis using min-3 sighting data significantly improved PIE v1 and HotSpotter performance, and especially CurvRank v2 performance, which more than doubles compared to the min-2 plot earlier in this report. The discrepancy is explained purely by the data used to make each plot: min-2 sightings or min-3, where the number 2 or 3 indicates the minimum number of photos per individual in the test set. Min-3 data has more photos per individual, and a smaller set of candidate individuals because of that filtering, than min-2 data. Previously reported Hotspotter and PIE v1 results from our report “Gray Whale Pose Invariant Embeddings (PIE v1) Results” on 3/11/21 were performed on a min-2 sighting basis versus the min-3 sighting results presented above. Our algorithms consistently perform better on min-3 sighting data, showing how (unlike manual matching that is often based on a single exemplar image) having more examples of an individual gives the computer vision system more information and greater ability to make the correct match. This pattern is not unique to gray whales or any of these particular models.

1.2.3 Standardized Performance Review Across Algorithms

Because Flukebook contains a multi-species, multi-feature, and multi-algorithm technical foundation [D], more than one algorithm can be run in parallel when trying to identify the individual animal in a photo.

Therefore across PIE v1, PIE v2, HotSpotter, and CurvRank v2, we created a standardized min-2 test set* (i.e. each individual considered need only have two annotations of a side) evaluated and plotted all algorithms and their combinations to suggest an optimal algorithm combination for deployment in Flukebook.org.

* The PIE training process needs min-3 photos per individual for algorithm training. However, for testing algorithm performance in general, only min-2 data are needed to ensure that every query image has at least one other image it could correctly match against. This also allows for more individuals to be considered for a more exhaustive top-N analysis because invariably more individuals are sighted at least twice than are sighted at least three times.

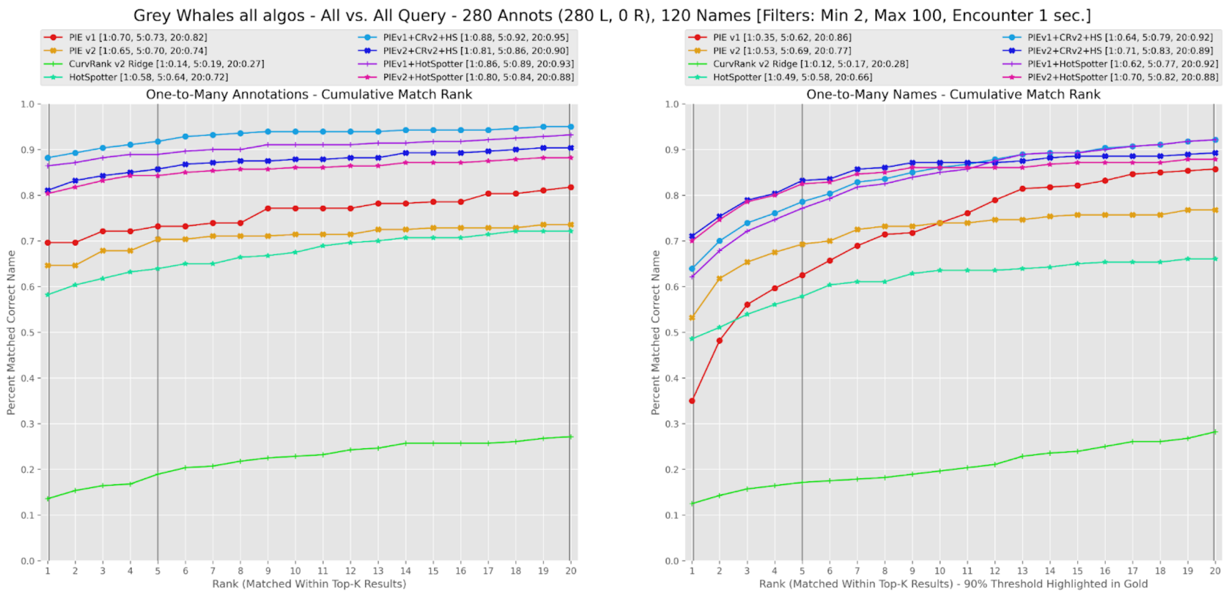


Figure 4. Top-n accuracy for all ID matching algorithms evaluated as well as their combined performance.

1.2.4 Recommended Algorithm Deployment in Flukebook.org

Based on the comparative results presented above, we recommend a minimum, default deployment configuration of PIE v2 and Hotspotter. PIE and HotSpotter offer significant complementary performance (i.e. each can significantly catch matches missed by the other) of top-1 71% and top-12 89%, while CurvRank v2 offered a minimal improvement to their results. While Wild Me is pleased that its own work with PIE v1 produced a model that modestly outperforms PIE v2 for gray whales in many cases, the technical compatibility of PIE v2 (PyTorch-based) provides a support incentive (i.e. PyTorch is much better at RAM management than TensorFlow, reducing overall support time and costs) and likely worth the trade-off in top-12 performance overall. However, PIE v1 and CurvRank v2 can also be available as selectable but non-default algorithms for the near future for evaluation and as a selectable, maximized configuration of PIE v1+Hotspotter+CurvRank v2 (top 1 70%, top-12 92%).

1.3 Opportunities for Further Development

1.3.1 Improving CurvRank v2

We were somewhat underwhelmed by the accuracy of the CurvRank v2 dorsal ridge matcher. As we see in the charts above, not only is it the poorest-performing matching algorithm we've deployed for gray whales, but it provides very little additional accuracy when combined with results from PIE and HotSpotter. Before this analysis was complete we had proposed further investment in CurvRank v2, but we now conclude that development resources would be better spent on other algorithms for this species.

1.3.2 Surveying time delta impacts on matchability

One striking feature of gray whale patterns is their gradual change over time, with new scars and markings appearing as the animals age. We work on pattern-based automated ID for a large number of species, and gray whales might be those whose patterns change the most; they contrast with e.g. zebras, whale sharks, or humpback whale flukes where identifiable pigmentation is more constant throughout the animal's life. This work with gray whales has inspired us to take change over time into account, investigating how the date of each sighting might be utilized to increase matching accuracy.

We would like to perform a number of experiments comparing temporality and matchability. To begin, we would investigate limiting match-against sets to photos taken within *N* years of each query photo. We suspect that, for the right value of *N*, matchers could be more accurate because we are not comparing temporally-distant photos where the same individual has significantly different patterns. We would therefore experiment to find if there exists an *N* where, by limiting matching sets in this way, we can get a more-accurate gray whale matcher. This would then be used in a match-against filter we would implement on Flukebook, so for example users could choose when starting a match if they are comparing all gray whales or only sightings within (for example) 5 years. Keeping both options available means we don't preclude matching for whales with large gaps between sightings.

If successful, this temporal filtering strategy would apply not only to PIE or HotSpotter (and CurvRank), but any matching algorithm, and other species as well as gray whales. By setting the aforementioned *N*-year filtering cutoff experimentally rather than a priori, we could account for different visual features changing at different rates, or even the sensitivity of different algorithms to that change. We could also re-compute that *N* after more datasets or new populations are added to Flukebook.

There are other temporal experiments that we have discussed internally, including incorporating each photo's timestamp as part of the input of a learning algorithm such as PIE. We will be raising this topic with our collaborator Professor Chuck Stewart at Rensselaer Polytechnic Institute, as it would make for a good subject of graduate research or a focused engagement by the Wild Me machine learning staff. And as is often the case, further avenues of investigation may present themselves as we do this work. However, for the scope of the next development investment we think this is a good starting point.

2 References

[A] Parham J, Stewart C, Crall JP, Rubenstein D, Holmberg J, and Berger-Wolf T. 2018. An Animal Detection Pipeline for Identification. 1075-1083. 10.1109/WACV.2018.00123.

[B] Wildbook Image Analysis (WBIA) Pipeline: https://docs.wildme.org/docs/researchers/ia_pipeline

[C] Crall JP, Stewart CV, Berger-Wolf TY, Rubenstein DI, and Sundaresan SR. 2013. HotSpotter-Patterned species instance recognition. In 2013 IEEE Workshop on Applications of Computer Vision, WACV 2013 (p. 230-237). [6475023] (Proceedings of IEEE Workshop on Applications of Computer Vision). https://doi.org/10.1109/WACV.2013.6475023

[D] Moskvyak O, et al. 2019. Robust Re-identification of Manta Rays from Natural Markings by Learning Pose Invariant Embeddings. https://arxiv.org/pdf/1902.10847.pdf

[E] Weideman HJ, Jablons ZM, Holmberg J, Flynn K, Calambokidis J, Tyson RB, Allen JB, Wells RS, Hupman K, Urian K, and Stewart CV. 2017. Integral Curvature Representation and Matching Algorithms for Identification of Dolphins and Whales. doi: 10.1002/ar.2365

Appendix A: AI for Gray Whales Q1 2021 Progress Report

Prepared for BOEM and NOAA

Wild Me made good progress in Q1 2021 toward the goals of the AI for Gray Whales project (Award 140M0120P0023).

A.1 Major Accomplishments (January-March 2021)

- Wild Me trained and evaluated PIE [4] machine learning individual ID model. Results are summarized below and covered exhaustively in this document. This task is now complete, and the model is fully available in the Flukebook.org platform.
- Wild Me's annotation team also recently completed the precursor dorsal ridge tracing that will be used to train CurvRank v2 [5]. A zip file of the visualizations of the tracings for that can be found here: https://drive.google.com/file/d/1scJUhkTthQI964R1c0JHNBO31obbdmUI/view?usp=sharing

A.2 PIE v1 Accuracy

The accuracy achieved on PIE v1 [1] for gray whales was:

- top-1: 43.0%
- top-5: 69.5%
- top-12: 81.6%.

This is validation accuracy, meaning that the validation data included no photos used during training.

A.3 PIE Comparison with HotSpotter pattern matcher

Used on humpback whales and many other species, the HotSpotter algorithm [3] differs from PIE in that it is a general, visual texture pattern matcher that is not trained or specialized for particular species. We compared the accuracy of HotSpotter to PIE on our left-side, 3-sighting gray whale validation images.

Results are summarized and further analyzed in this document.

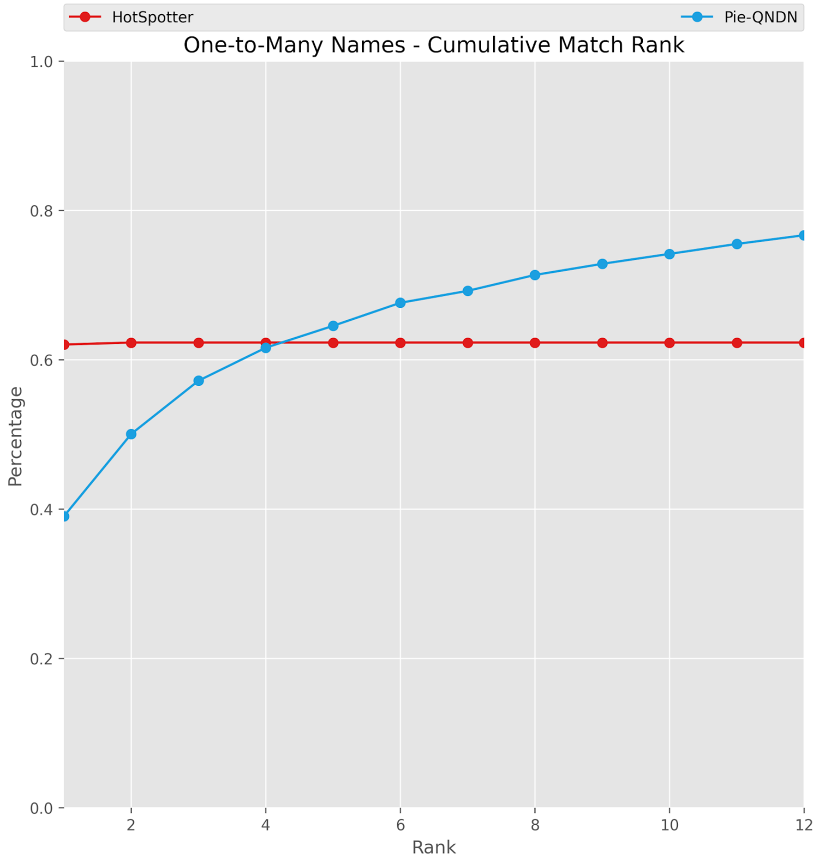


Figure A1. PIE vs. HotSpotter initial evaluation

A.4 Next Up: CurvRank v2

With both PIE and HotSpotter now deployed on Flukebook, our focus will shift to training the CurvRank v2 algorithm on traced dorsal ridges and evaluating its predictive accuracy on CRC data. Dorsal ridge tracing has already been completed.

Appendix B: Gray Whale Pose Invariant Embeddings (PIE v1) Results

3/11/2021

B.1 Training Data

The training data was provided by Cascadia Research Collective and represents their gray whale catalog. Only IDs and photos were consistently provided. At our request, prior to training they did a manual review of the IDs to minimize possible labeling errors, where a researcher reviewed every photo for every name to confirm an accurate ID label. Filtering for only the whales with at least 3 sightings (a requirement for PIE training and validation), we had 2,012 right-side and 1,878 left-side photos of 359 identified individuals.

When PIE is used on lateral views, we mirror every right-side image so that each picture PIE sees looks like a left-side image, ensuring the model is always seeing a standard orientation. During matching, viewpoints are already labeled and we do not compare rights to lefts or vice versa. This gives us several options for how to handle rights versus lefts in training. We explored training on all 3,890 right- and left-images in one go, splitting each individual into a right-name and a left-name so that the system does not confuse the two sides, but this did not improve validation accuracy over models trained on only one side. A possible reason for this is that the edge contour, which unlike the patterning is shared by both sides, is influencing PIE's match rankings. We ultimately trained our model on all the right-side photos, leaving out the left-side photos from training to provide the robust validation accuracy numbers reported here.

B.2 PIE v1 Accuracy

The accuracy achieved on PIE v1 [1] for gray whales was:

- top-1: 43.0%
- top-5: 69.5%
- top-12: 81.6%.

This is validation accuracy, meaning that the validation data included no photos used during training.

Because these figures are lower than our preconceived expectations of matchability with PIE v1 (i.e. lower than was seen with this algorithm on right whale laterals but comparable to orca laterals), we investigated several hypotheses for why this species/data is more challenging.

Pattern change over time

Since the matchable patterns are heavily scar-based, we suspected that their change over time could explain this lower accuracy. Our investigations showed mixed support for this hypothesis. Looking at 1329 timestamped validation photos of 273 individuals (each individual has at least 3 photos in this set), we looked at two data points: the time delta between a query photo and its (temporally) nearest correct candidate match, which we will call min_tdelta; and the mean time delta between a query photo and all of its correct candidate matches, which we will call mean_tdelta.

For the 1329 timestamped validation photos, we divided them into two sets: the 1221 photos that were matched with rank <= 36, and the remaining 108 photos that were not matched correctly. Both min_tdelta and mean_tdelta are on average lower among the matched photos:

	mean min_tdelta	median min_tdelta	mean mean_tdelta	median mean_tdelta
matchable photos (n=1,221)	313 days	139 days	829 days	686 days
unmatchable photos (n=108)	572 days	388.5 days	1061 days	798 days
Mann-Whitney U-test null hypothesis p value*	p = 2.76 *10^-7 *(U = 46,792; n1*n2 = 131,868)*		p = 0.0046 *(U = 55,995; n1*n2 = 131,868)*	

*: We performed a two-tailed Mann-Whitney U-test on the two distributions (matchable tdeltas vs. unmatchable tdeltas) for each measure, which tests the null hypothesis that, if we randomly selected a matchable and an unmatchable photo, neither is more likely to have a higher tdelta than the other. In both cases, the low p value indicates that unmatchable photos generally have higher tdeltas than matchable photos, especially looking at min_tdelta. This supports our intuition that photos with a large min_tdelta are difficult to match.

However, among photos that *are* matchable, there is very little correlation between the match rank and min_tdelta, with a positive correlation between these two variables (as we would expect) but an R^2 value of only 0.01, as shown in the chart below. This relationship also exists in mean_tdelta but with an even lower R value.

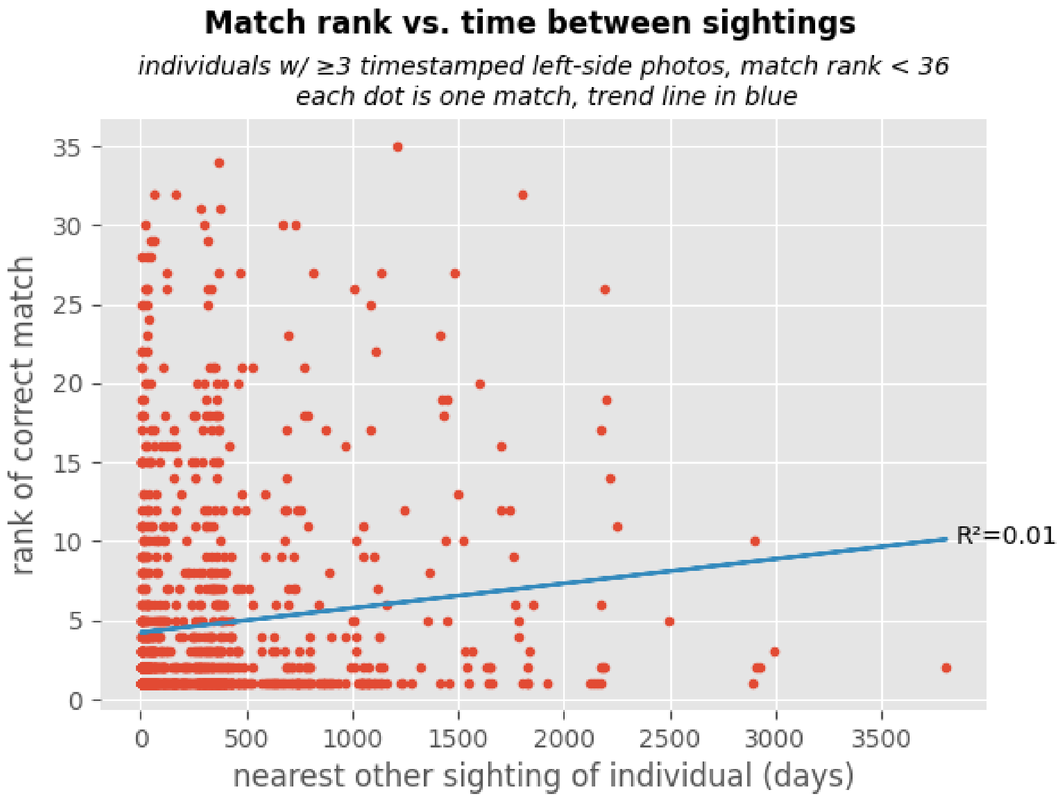
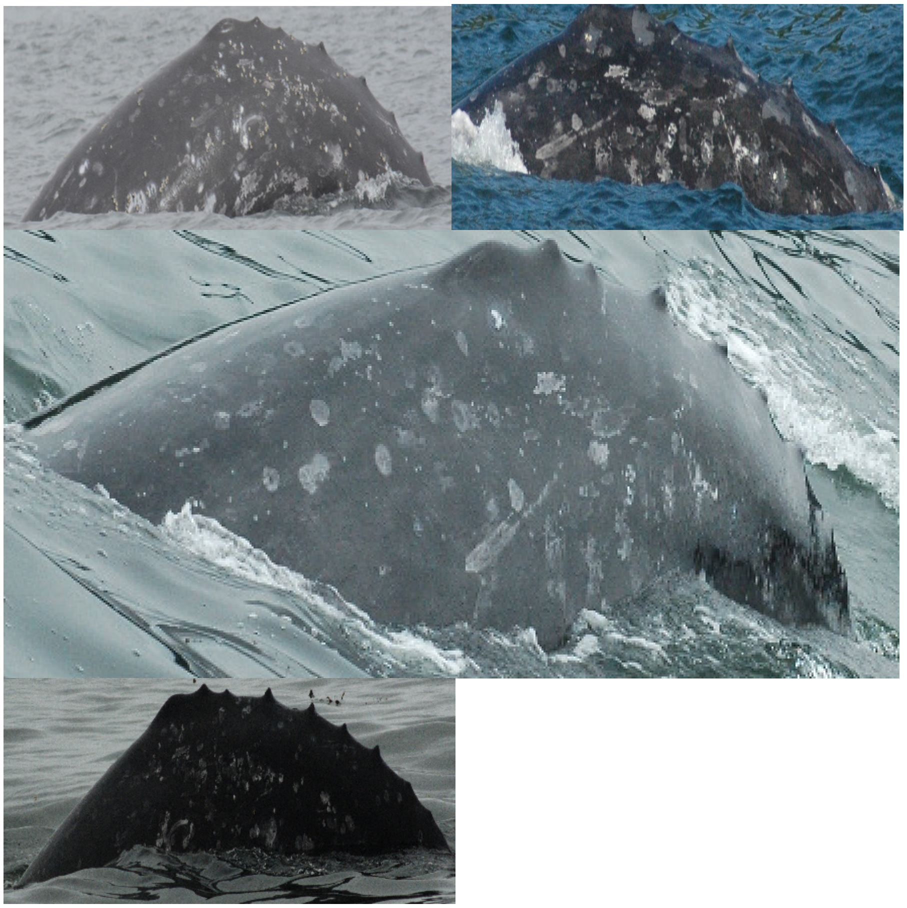


Figure B1. Match rank vs. time between sightings

These two results are contraindicative. Photos that are not matchable generally have higher tdeltas than those that are matchable, but this does not appear to affect at what rank a correct match appears (a rough measure of "how matchable" a matchable photo is). We believe that change over time is a significant explanation for the PIE accuracy we are seeing, though it is not a perfect or complete explanation.

Pattern variability vs. ridge contour consistency

We have heard from researchers at Cascadia Research Collective that the dorsal ridges, posterior of the dorsal fin, are more effective than patterns for matching these animals. We noticed several supporting examples of these among the unmatched validation images (examples below). Two things we notice are how distinct the ridges are and how variable the patterns are, making it difficult for a human (and we believe PIE as well) to identify which parts of the pattern are useful for matching.
The large image is a query that failed to match any candidates; the three smaller images are the correct candidates of the same individual that PIE failed to identify. The ridge seems more distinctive than the changing patterns.



The example below highlights how gray whales show a lot of visual pattern, but that pattern can vary greatly from encounter to encounter. The distinctive patterning in the smaller photos is not shared in the larger photo that failed to match with PIE. We believe PIE is struggling to distinguish between relevant and irrelevant patterns for matching purposes. The dorsal ridge seems the more effective way to match this individual.

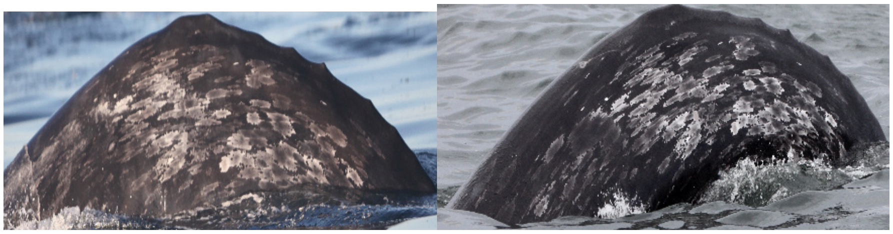
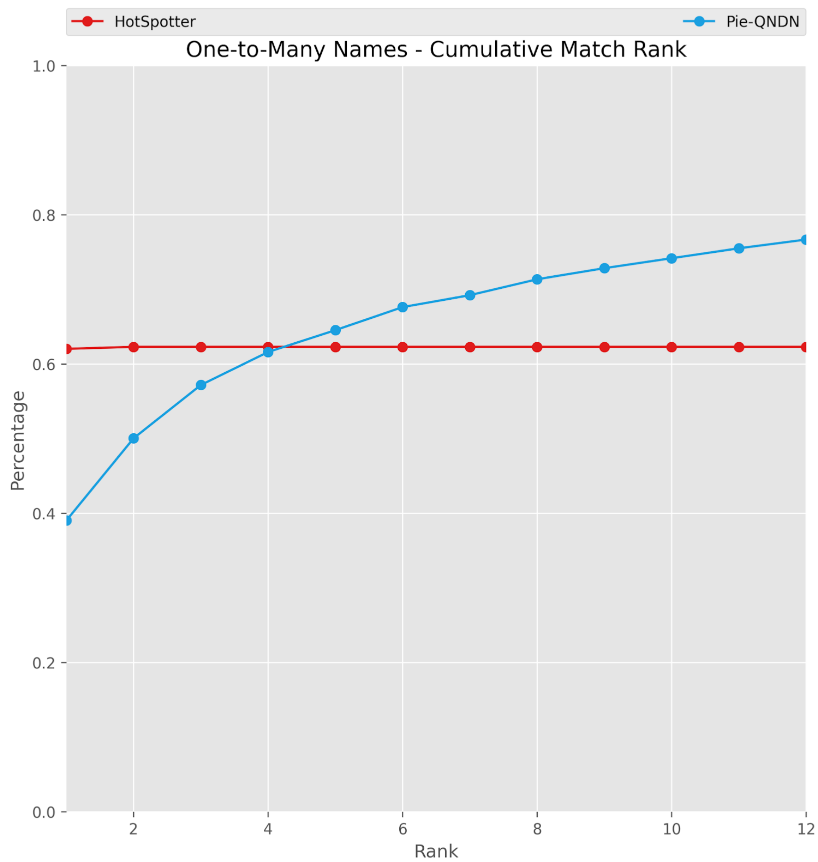


Figure B2. Visual review of patterning changes with time

Subsequent experiments with the CurvRank edge-contour matching algorithm will show how much this improves the overall matching system alongside this PIE algorithm.

B.3 Comparison with HotSpotter pattern matcher

Used on humpback whales and many other species, the HotSpotter algorithm [2] differs from PIE in that it is a general, visual texture pattern matcher that is not trained or specialized for particular species. We compared the accuracy of HotSpotter to PIE on our left-side, 3-sighting gray whale validation images.



We see that HotSpotter has a higher rank-1 accuracy of 62% and lower accuracy at ranks 5 and above compared to PIE. HotSpotter has remarkably consistent matching, and on this data it either finds a match correctly at rank 1 or it fails to find a match at any rank. We have seen HotSpotter behave this way on many several species including orcas. In contrast, PIE has a more intuitive shape of the accuracy-rank curve and can find matches at every rank, with fewer matches at each higher rank, but of course higher cumulative accuracy.

Both HotSpotter and PIE are now available for use on Flukebook and can be started concurrently for any gray whale query image.

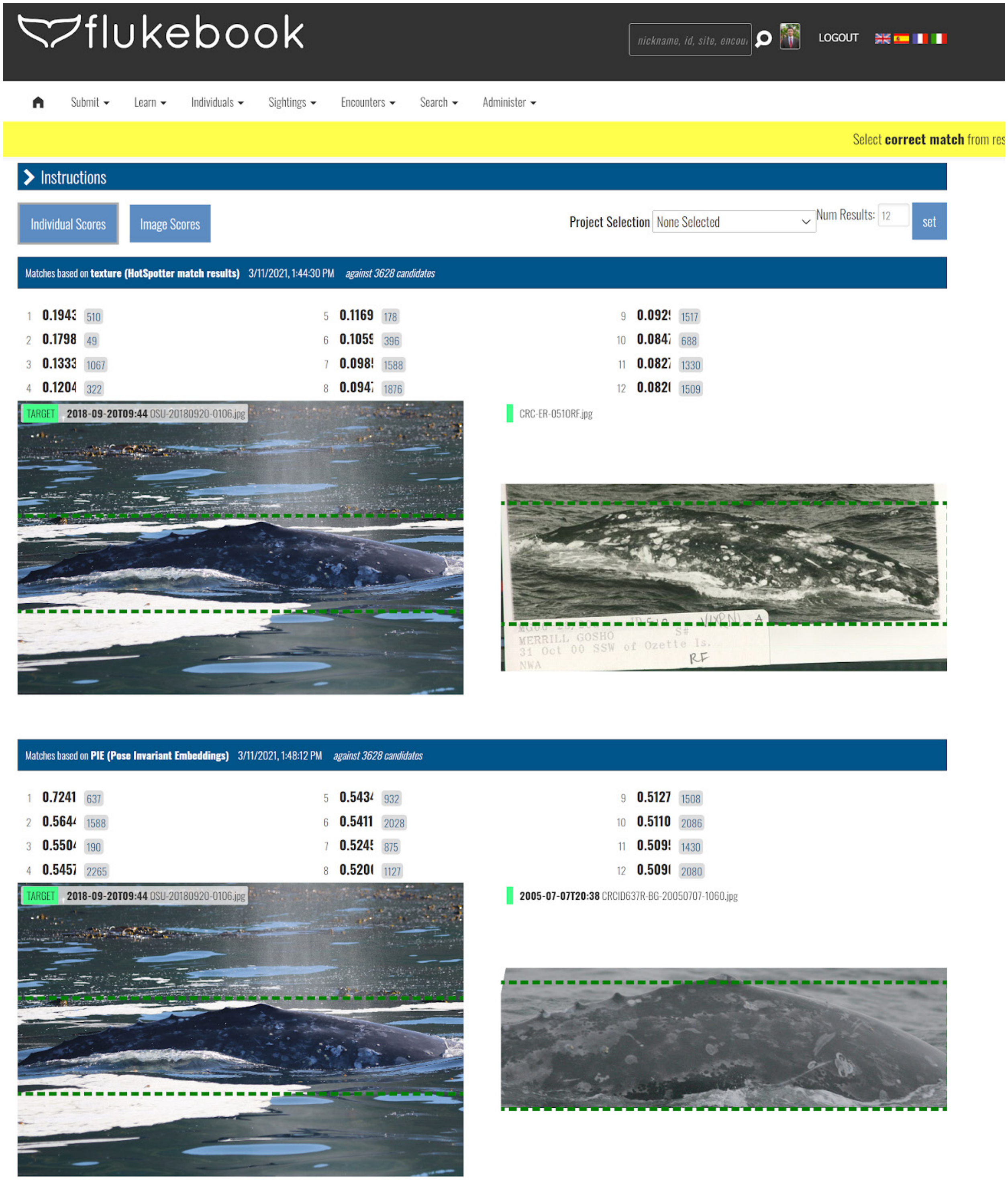


Figure B3. An example match result in Flukebook. Both HotSpotter and PIE have been deployed and can be run in tandem. In this example, PIE successfully predicts the correct match in rank 1 while HotSpotter does not find. [Link to result.]

B.4 Next Up: CurvRank v2

With both PIE and HotSpotter now deployed on Flukebook, our focus will shift to training the CurvRank v2 algorithm [3] on traced dorsal ridges and evaluating its predictive accuracy on CRC data. Dorsal ridge tracing has already been completed.

B.5 Potential: PIE v2

In our ongoing work on other species with Olga Moskvyak, we learned that a second generation PIE v2 algorithm has been developed. It has already proven to exceed PIE v1 significantly for another species. Wild Me has already begun integration of PIE v2. While a new PIE v2 model is not promised under this contract, we do anticipate re-evaluating these PIE results in the near future and presenting the revised results.

Appendix C: AI for Gray Whales Q4 Progress Report

Prepared for BOEM and NOAA

Wild Me made good progress in Q4 2020 toward the goals of the AI for Gray Whales project (Award 140M0120P0023).

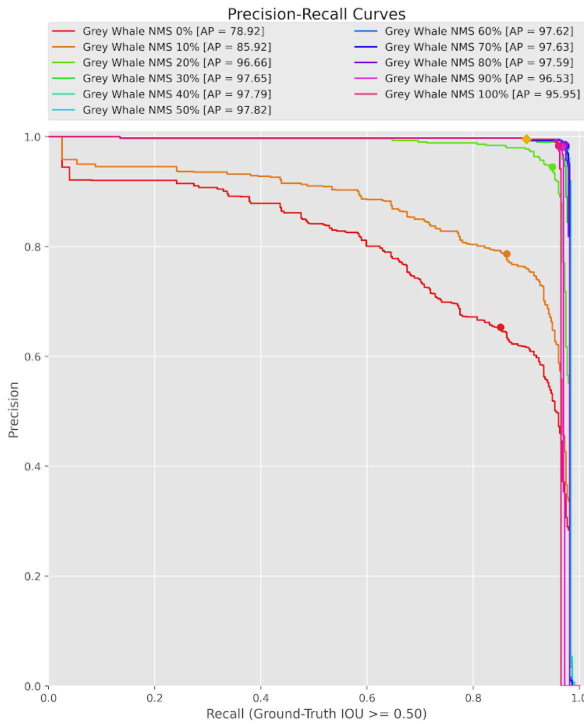
C.1 Major Accomplishments (Sept-Dec 2020)

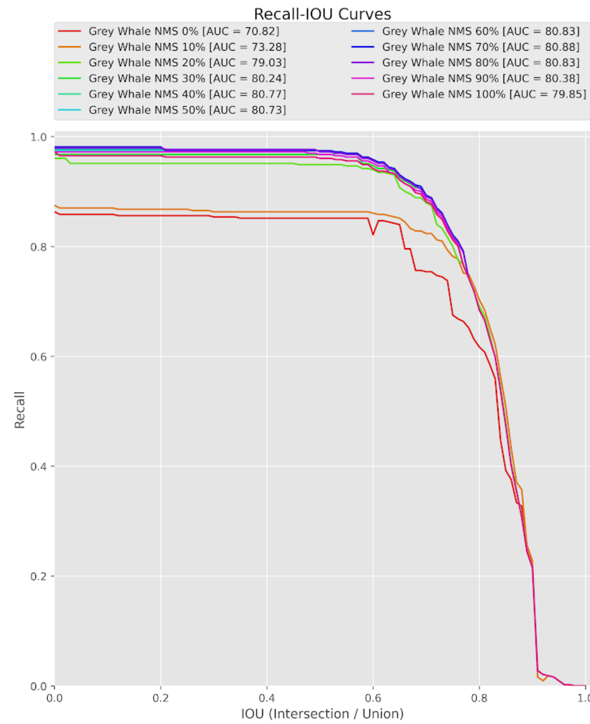
The following major accomplishments occurred in Q4 2020:

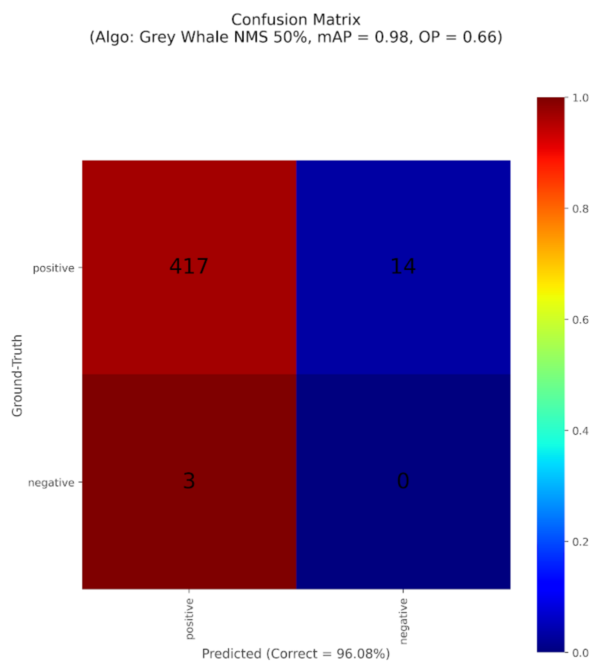
- Project post-award meeting occurred on 9/15/2020. Meeting summary follows this report.
- Wild Me attended and presented at a Project Kick-off Meeting on September 30th.
- Discussions around data and data sharing were conducted at two gray whale working group meetings on Oct. 5th and 30th, which included a broader array of project participants. Project notes are included with this report.
- Wild Me received the following data sets and incorporated subsets into our annotation interface machine learning detector training:
  - CRC gray whale catalog, including photos and IDs. Metadata (where/when) was incomplete but unnecessary for this project.
  - Sample photos representing field conditions during data collection by the Makah Tribe
  - Data from Sergio at LSIESP
- Wild Me hand annotated 2085 images from across the data sets provided. 2182 annotations (bounding boxes) were made, representing some photos with >1 whale. A video of the process can be found at: https://youtu.be/rS5lmQKjceE
- Wild Me started training the machine learning-based detector model that will run in the Wildbook Image Analysis pipeline [1][2].

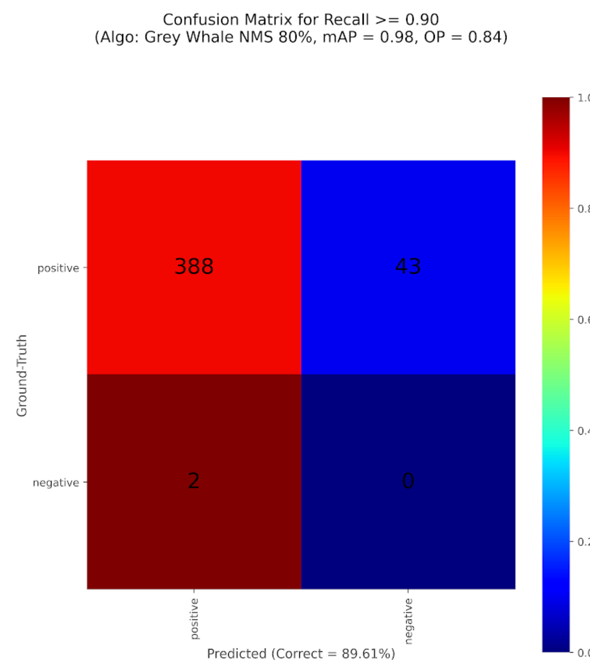
C.2 Major Accomplishments (January 2020)

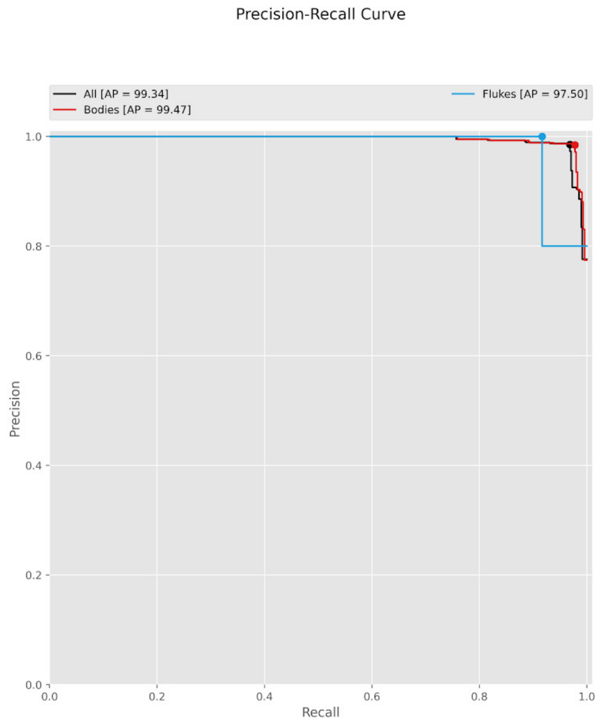
- Wild Me completed detector model training on January 14th. Precision and recall curves are visualized here.

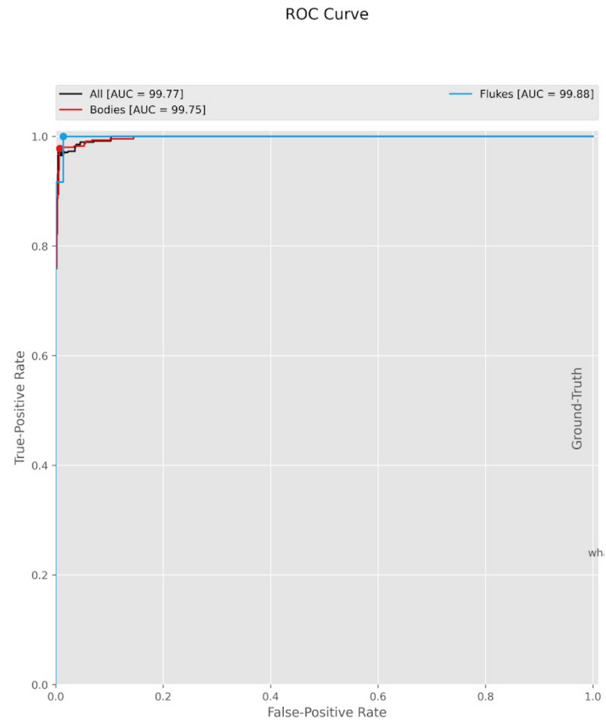

Precision-Recall Curves
Grey Whale NMS 0% [AP = 78.92]
Grey Whale NMS 10% [AP = 85.92]
Grey Whale NMS 20% [AP = 96.66]
Grey Whale NMS 30% [AP = 97.65]
Grey Whale NMS 40% [AP = 97.79]
Grey Whale NMS 50% [AP = 97.82]
Grey Whale NMS 60% [AP = 97.62]
Grey Whale NMS 70% [AP = 97.63]
Grey Whale NMS 80% [AP = 97.59]
Grey Whale NMS 90% [AP = 96.53]
Grey Whale NMS 100% [AP = 95.95]
Precision
Recall (Ground-Truth IOU >= 0.50)


Recall-IOU Curves
Grey Whale NMS 0% [AUC = 70.82]
Grey Whale NMS 10% [AUC = 73.28]
Grey Whale NMS 20% [AUC = 79.03]
Grey Whale NMS 30% [AUC = 80.24]
Grey Whale NMS 40% [AUC = 80.77]
Grey Whale NMS 50% [AUC = 80.73]
Grey Whale NMS 60% [AUC = 80.83]
Grey Whale NMS 70% [AUC = 80.88]
Grey Whale NMS 80% [AUC = 80.83]
Grey Whale NMS 90% [AUC = 80.38]
Grey Whale NMS 100% [AUC = 79.85]
Recall
IOU (Intersection / Union)


Confusion Matrix
(Algo: Grey Whale NMS 50%, mAP = 0.98, OP = 0.66)
Ground-Truth
positive
negative
417
14
3
0
Predicted (Correct = 96.08%)


Confusion Matrix for Recall >= 0.90
(Algo: Grey Whale NMS 80%, mAP = 0.98, OP = 0.84)
Ground-Truth
positive
negative
388
43
2
0
Predicted (Correct = 89.61%)


Precision-Recall Curve
All [AP = 99.34]
Bodies [AP = 99.47]
Flukes [AP = 97.50]
Precision
Recall
0.0
0.2
0.4
0.6
0.8
1.0


ROC Curve
All [AUC = 99.77]
Bodies [AUC = 99.75]
Flukes [AUC = 99.88]
True-Positive Rate
False-Positive Rate
Ground-Truth
0.0
0.2
0.4
0.6
0.8
1.0

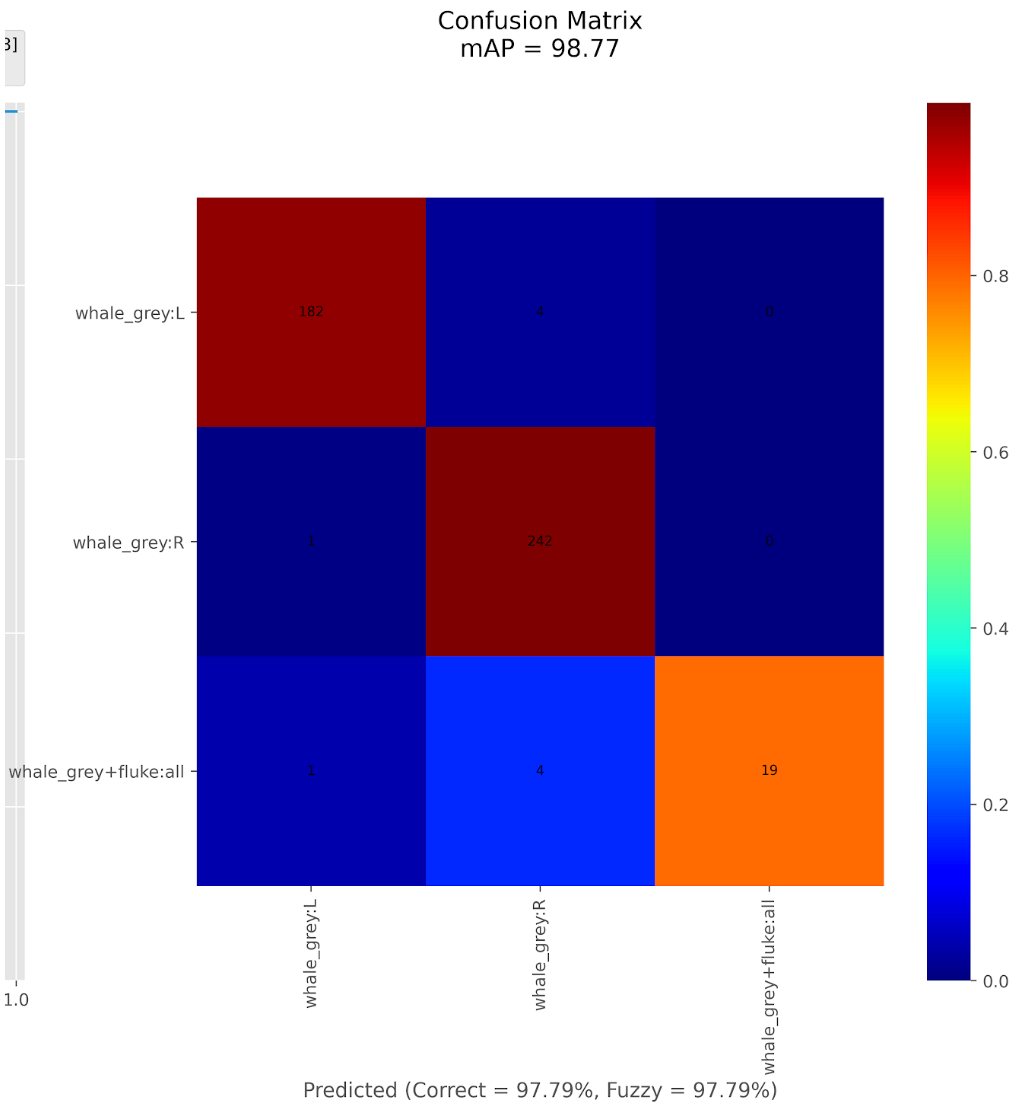


Figure C1. Machine learning detector performance visualization

We have provided visualizations of the training, which includes a background masking ML stage. Here is a zip with rich examples: https://drive.google.com/file/d/18EILvknV3v79JcxxffAz8y7En1bUP7zJ/view?usp=sharing

- On January 25, 2021, Wild Me completed detector model integration into Flukebook.org and imported the CRC catalog of IDs and photos, running the detector to create Annotations (i.e. bounding boxes) for each whale in each photo. With this integration, the HotSpotter [3] algorithm was primed (texture features extracted) and is now available for matching in Flukebook.org. A video demonstrates this progress: [https://youtu.be/YFRJlRWsbQ4.](https://youtu.be/YFRJlRWsbQ4)

- Trevor Joyce (NOAA), CRC staff, and Jake Levenson (BOEM) have been provided with access to review data and HotSpotter matching.
- CRC staff and NOAA personnel were provided with a data review interface to ensure accurate data is used for subsequent project ML training with PIE [4] and CurvRank v2 [5]: https://docs.google.com/spreadsheets/d/1eS_ACzY-4BrEOp8KGp6lV_CCjrj6Rr08bdURL9NulZQ/edit?usp=sharing

C.3 Upcoming Developments

- Wild Me will start PIE training February 8, 2021.
- CurvRank v2 training is expected to start early March 2021.

C.4 Contact Information

For additional questions and clarifications, please contact:

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jason@wildme.org

C.5 References

[1] Parham, Jason & Stewart, Charles & Crall, J.P. & Rubenstein, Daniel & Holmberg, Jason & Berger-Wolf, Tanya. (2018). An Animal Detection Pipeline for Identification. 1075-1083. 10.1109/WACV.2018.00123.

[2] Wildbook Image Analysis (WBIA) Pipeline: https://docs.wildme.org/docs/researchers/ia_pipeline

[3] Crall, J. P., Stewart, C. V., Berger-Wolf, T. Y., Rubenstein, D. I., & Sundaresan, S. R. (2013). HotSpotter-Patterned species instance recognition. In 2013 IEEE Workshop on Applications of Computer Vision, WACV 2013 (pp. 230-237). [6475023] (Proceedings of IEEE Workshop on Applications of Computer Vision). https://doi.org/10.1109/WACV.2013.6475023

[4] Moskvyak O. et al. 2019 Robust Re-identification of Manta Rays from

Natural Markings by Learning Pose Invariant Embeddings. https://arxiv.org/pdf/1902.10847.pdf

[5] Weideman, H.J, Z.M. Jablons, J. Holmberg, K. Flynn, J. Calambokidis, R. B. Tyson, J.B. Allen, R.S. Wells, K. Hupman, K. Urian, C.V. Stewart. 2017. Integral Curvature Representation and Matching Algorithms for Identification of Dolphins and Whales. doi: 10.1002/ar.2365

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