Shark Detection Classification

CS 4624: Multimedia, Hypertext and Information Access
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Outline

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- Design and Implementation: Machine Learning
- Testing and Results: Database
- Testing and Results: Machine Learning
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- Future Work
- Acknowledgements
- References
Roles

- Database Team
  - Jack Golden, Nicholas Cho
- Machine Learning Team
  - Alfred Premkumar, Charan Srinivasan
Problem and Objectives

● Client: Dr. Francesco Ferretti
  ○ SharkPulse: Uses computer vision and machine learning to locate and classify shark species from visual media.

● Objectives:
  ○ Database Objective
    ■ Merge collection databases and create pipeline to training data table (PSQL)
  ○ Model Objective
    ■ Increase overall classification accuracy by 5-10%.
    ■ Increase number of species identified (currently 47)
Data team merged new validation monitor images into existing training data table.

- Previous Training Table: 66794 images
- New Training Table: 73119 images

Table automatically updates when web scrapers add new entries.

<table>
<thead>
<tr>
<th>Image Name</th>
<th>Species</th>
<th>Genus</th>
</tr>
</thead>
<tbody>
<tr>
<td>GreatWhite.jpg</td>
<td>Carcharodon carcharias</td>
<td>Carcharodon</td>
</tr>
<tr>
<td>Hammerhead.jpg</td>
<td>Sphyrrna mokarran</td>
<td>Sphyrrna</td>
</tr>
<tr>
<td>TigerShark.jpg</td>
<td>Galeocerdo cuvier</td>
<td>Galeocerdo</td>
</tr>
<tr>
<td>NurseShark.jpg</td>
<td>Ginglymostoma cirratum</td>
<td>Ginglymostoma</td>
</tr>
</tbody>
</table>

Table 3: Training Table Schema
Design and Implementation: Database

- Collected and merged 6484 unique records into our training table.

```
CREATE TABLE merge_v3 AS TABLE training
WITH NO DATA;
CREATE TABLE AS
pelagic-> INSERT INTO merge_v3
(img_name, species)
(
SELECT img_name, species_name FROM sharkpulse WHERE validated = 'true'
);
INSERT 0 528
pelagic-> INSERT INTO merge_v3
(img_name, species)
(
SELECT img_name, species_name_1 FROM dataMining WHERE validated
);
INSERT 0 2243
pelagic-> INSERT INTO merge_v3
(img_name, species)
(
SELECT img_name, species_name FROM Instagram WHERE validated
);
INSERT 0 3713
```

PSQL query: Table Creation

```
UPDATE merge_v3
SET genus = split_part(species,' ',1)
;
UPDATE 6484
```

PSQL query: Updating genus attributes

```
pelagic-> INSERT INTO training_backup_new
(img_name, genus, species)
(
SELECT DISTINCT(img_name), genus, species FROM merge_v3
);
INSERT 0 6328
pelagic-> SELECT COUNT(img_name) FROM training_backup_new;
count
---------
73119
(1 row)
```
Design and Implementation: Machine Learning

- Layered Model:
  - Detection: Locate Shark
  - Classification: Shark or Not?
  - Classification: Shark genus?
  - Classification: Shark species?

- Goal: Update the classification models to Vision Transformer Models.
Design and Implementation: Machine Learning

- Tools: Keras, Tensorflow, VIT-Keras
- 3 training files: train_SI_vit.py, train_gen_vit.py, train_spec_vit.py
- Data threshold:
  - 900 images for genus, 400 for species, otherwise gets put into “other”
  - 80/20 Training/Testing Split, of the training: 80/20 Training/Validation Split
- Data breakdown:

<table>
<thead>
<tr>
<th>Model</th>
<th>Training Data (images)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shark Identifier</td>
<td>117060</td>
</tr>
<tr>
<td>Genus Classifier</td>
<td>41724</td>
</tr>
<tr>
<td>Species Classifiers</td>
<td>32109</td>
</tr>
</tbody>
</table>
**Testing and Results: Machine Learning**

- Data is split 80/20 for training data and testing data.
- During training, cross validation is performed at each epoch with a 80/20 split of training data.
- After the model is formed, it is used to predict labels from the testing data, which are then compared to the actual labels.

<table>
<thead>
<tr>
<th>precision</th>
<th>recall</th>
<th>f1-score</th>
<th>support</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.98</td>
<td>0.95</td>
<td>10052</td>
</tr>
<tr>
<td>1</td>
<td>0.95</td>
<td>0.99</td>
<td>13361</td>
</tr>
</tbody>
</table>

- accuracy: 0.96
- macro avg: 0.96
- weighted avg: 0.96
Testing and Results: Machine Learning

Overall Shark Identification Accuracy: 96%
Testing and Results: Machine Learning

Overall Shark Genus Classification Accuracy: 72%
Testing and Results: Machine Learning

Average Shark Genus-specific Species Classification Accuracy: 74%

- 27 Genera able to be classified
  - (Up from 26)
- 51 Species able to be classified
  - (Up from 48)

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Accuracy (%)</th>
<th>Classifier</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alopias</td>
<td>80</td>
<td>Hexanchus</td>
<td>56</td>
</tr>
<tr>
<td>Brachacahrus</td>
<td>95</td>
<td>Hydrolagus</td>
<td>94</td>
</tr>
<tr>
<td>Carcharhinus</td>
<td>68</td>
<td>Isurus</td>
<td>64</td>
</tr>
<tr>
<td>Carcharias</td>
<td>100</td>
<td>Mustelhus</td>
<td>62</td>
</tr>
<tr>
<td>Carcharodon</td>
<td>100</td>
<td>Negaprion</td>
<td>29</td>
</tr>
<tr>
<td>Cephaloscyllium</td>
<td>70</td>
<td>Orectolobus</td>
<td>97</td>
</tr>
<tr>
<td>Cetorhinus</td>
<td>100</td>
<td>Prionace</td>
<td>100</td>
</tr>
<tr>
<td>Echinorhinus</td>
<td>89</td>
<td>Rhincodon</td>
<td>100</td>
</tr>
<tr>
<td>Galeocerdo</td>
<td>100</td>
<td>Scylorhinus</td>
<td>52</td>
</tr>
<tr>
<td>Galeorhinus</td>
<td>100</td>
<td>Sphyrna</td>
<td>40</td>
</tr>
<tr>
<td>Galeus</td>
<td>100</td>
<td>Squalus</td>
<td>68</td>
</tr>
<tr>
<td>Ginglymostoma</td>
<td>88</td>
<td>Triacodon</td>
<td>100</td>
</tr>
<tr>
<td>Haploblepharus</td>
<td>89</td>
<td>Triakis</td>
<td>99</td>
</tr>
<tr>
<td>Heterodentus</td>
<td>94</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Average (no single-species)</strong></td>
<td><strong>74</strong></td>
<td><strong>Average</strong></td>
<td><strong>83</strong></td>
</tr>
</tbody>
</table>

Table 6: Classification Accuracy of Genus-specific Species Classifier
Testing and Results: Machine Learning

<table>
<thead>
<tr>
<th>Model</th>
<th>Testing Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Old Shark Identifier</td>
<td>90%</td>
</tr>
<tr>
<td>New Shark Identifier</td>
<td>96%</td>
</tr>
<tr>
<td>Old Shark Genus Classification*</td>
<td>70%</td>
</tr>
<tr>
<td>New Shark Genus Classification</td>
<td>72%</td>
</tr>
<tr>
<td>Old Shark Species Classification*</td>
<td>70%</td>
</tr>
<tr>
<td>New Shark Species Classification (average)</td>
<td>74%</td>
</tr>
</tbody>
</table>

*The old genus and species classifiers were used in tandem, and should not be directly compared to.*
Challenges / Lessons Learned

- Training sometimes crashed due to server capacity. Resolved by tuning hyperparameters as well as monitoring the training while it is happening.
- Difficulty navigating PSQL database + confusion over the flow of data. Resolved by asking clarifying questions to Jenrette / Ferretti.
- Weekly meetings and frequent communication with our client was key to the success of our team.
Future Work

- Techniques to fetch a larger volume of shark data
- Further hyperparameter tuning for model training
- Decreasing training time for each model
- Moving models into a production environment
Acknowledgements

Francesco Ferretti
Jeremy Jenrette
Edward Fox
http://sp2.cs.vt.edu/ (sharkpulse website)

J. Jenrette, Z. Y.-C. Liu, P. Chimote, T. Hastie, E. Fox, F. Ferretti, *Shark detection and classification with machine learning*, Ecological Informatics, Volume 69, 2022, 101673, ISSN 1574-9541,

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