

Shark Detection Classification



CS 4624: Multimedia, Hypertext and
Information Access

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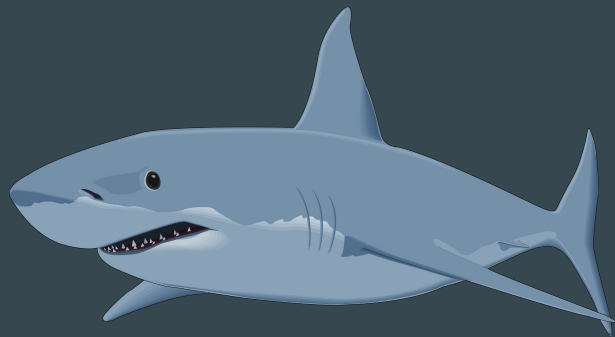
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Alfred Premkumar
Nicholas Cho
Charan Srinivasan

Outline

- Roles
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- Design and Implementation: Database
- Design and Implementation: Machine Learning
- Testing and Results: Database
- Testing and Results: Machine Learning
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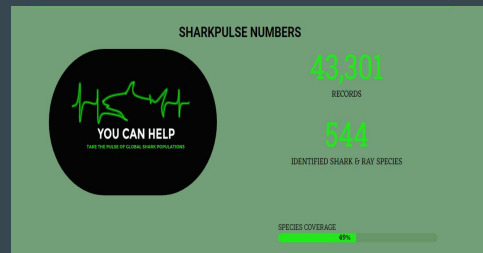
Roles

- 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)



Design and Implementation: Database

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.

Image Name	Species	Genus
GreatWhite.jpg	Carcharodon carcharias	Carcharodon
Hammerhead.jpg	Sphyrna mokarran	Sphyrna
TigerShark.jpg	Galeocerdo cuvier	Galeocerdo
NurseShark.jpg	Ginglymostoma cirratum	Ginglymostoma

Table 3: Training Table Schema



SharkPulse Database

Design and Implementation: Database

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

```
pelagic=> 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 data_mining 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

PSQL query: Updating genus attributes

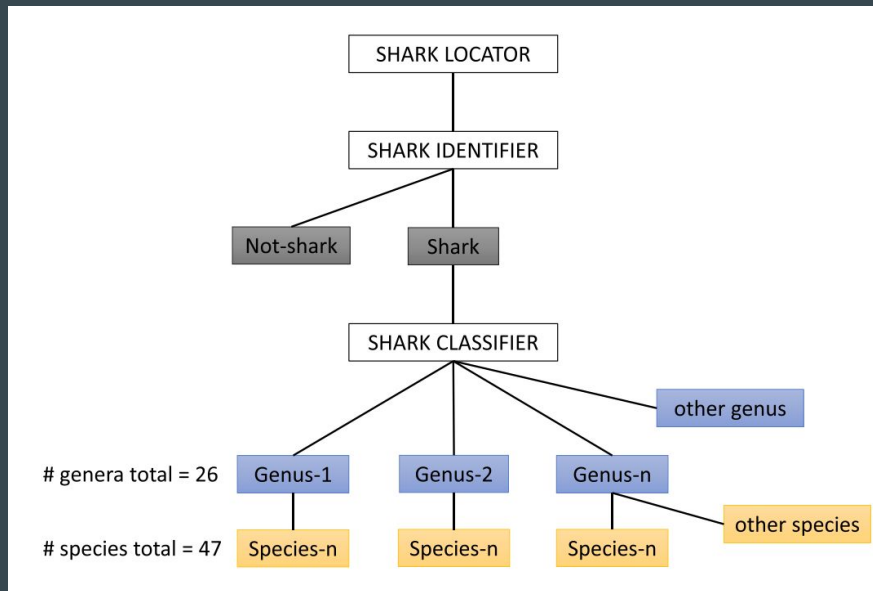
```
pelagic=> UPDATE merge_v3
SET genus = split_part(species, ' ', 1)
;
UPDATE 6484
```

```
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:

Model	Training Data (images)
Shark Identifier	117060
Genus Classifier	41724
Species Classifiers	32109

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

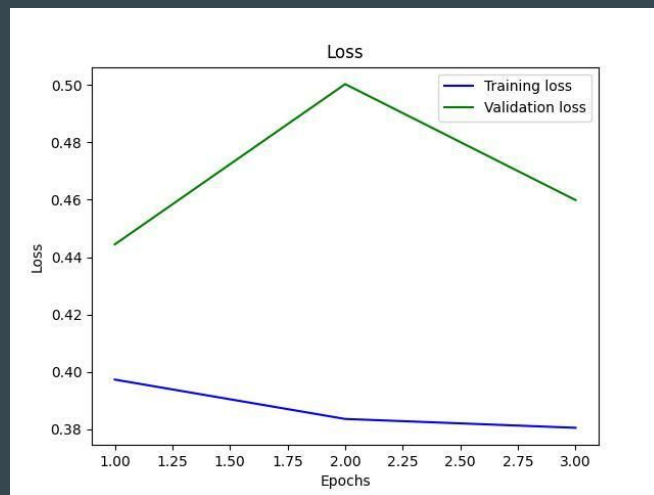
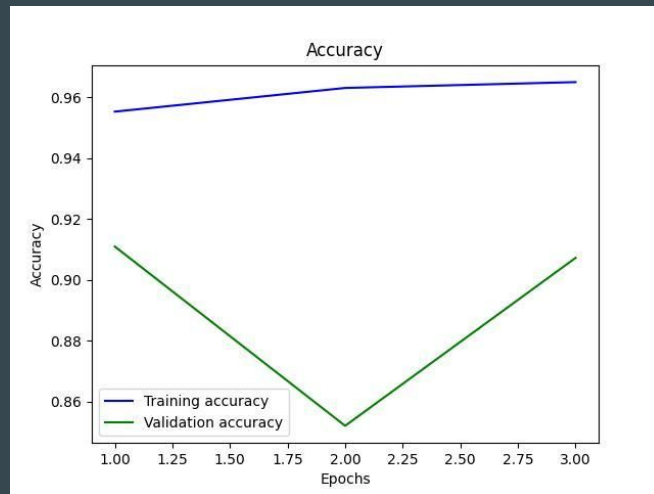
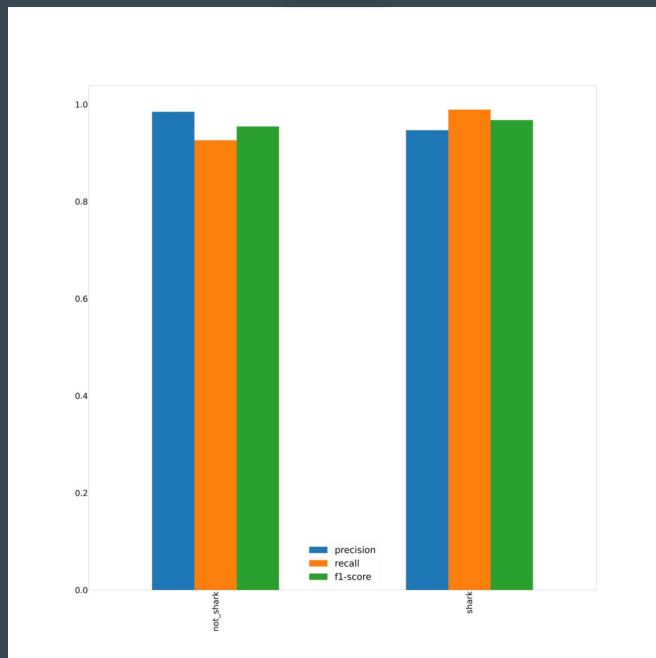
```
You may not need to update to CUDA 11.1; cherry-picking the ptxas binary is often sufficient.  
1017/1017 [=====] - 881s 834ms/step - loss: 2.9265 - accuracy: 0.1647 - val_loss: 2.8648 - val_accuracy: 0.1745
```

- After the model is formed, it is used to predict labels from the testing data, which are then compared to the actual labels

	precision	recall	f1-score	support
0	0.98	0.93	0.95	10052
1	0.95	0.99	0.97	13361
accuracy			0.96	23413
macro avg	0.97	0.96	0.96	23413
weighted avg	0.96	0.96	0.96	23413

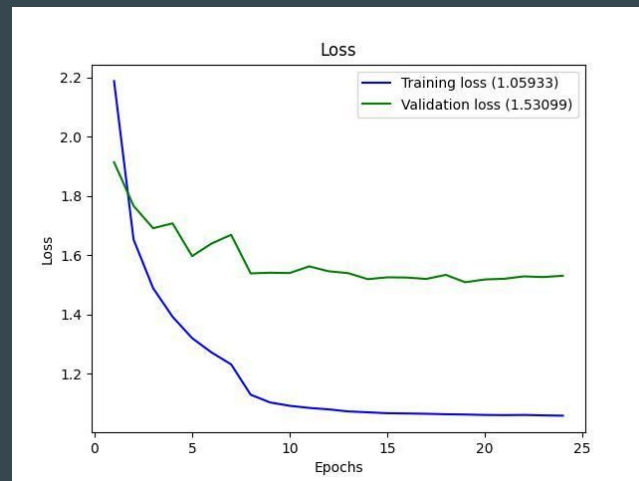
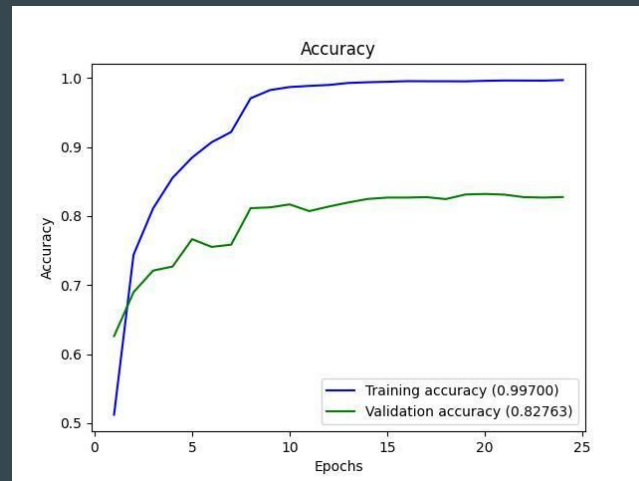
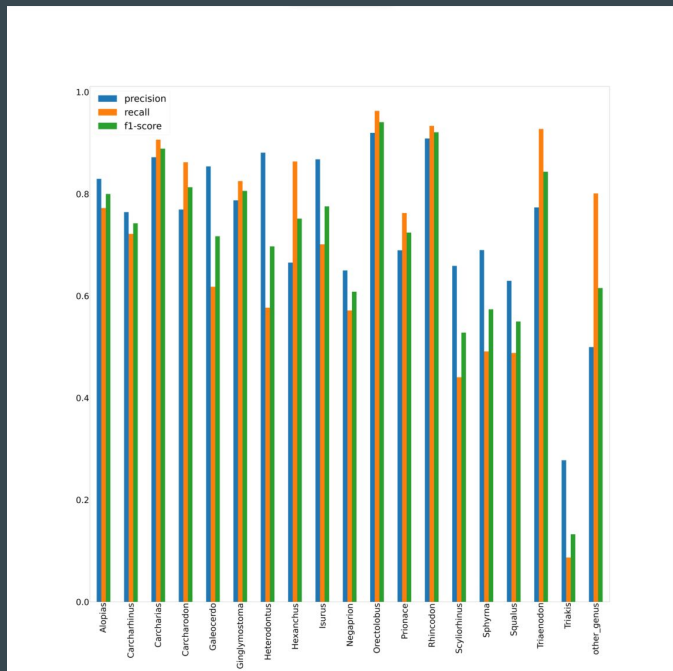
Testing and Results: Machine Learning

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)

Classifier	Accuracy(%)	Classifier	Accuracy (%)
Alopias	80	Hexanchus	56
Brachaelurus	95	Hydrolagus	94
Carcharhinus	68	Isurus	64
Carcharias	100	Mustelus	62
Carcharodon	100	Negaprion	29
Cephaloscyllium	70	Orectolobus	97
Cetorhinus	100	Prionace	100
Echinorhinus	89	Rhincodon	100
Galeocerdo	100	Scyliorhinus	52
Galeorhinus	100	Sphyrna	40
Galeus	100	Squalus	68
Ginglymostoma	88	Triacnodon	100
Haploblepharus	89	Triakis	99
Heterodontus	94		
Average (no single-species)	74	Average	83

Table 6: Classification Accuracy of Genus-specific Species Classifier

Testing and Results: Machine Learning

Model	Testing Accuracy
Old Shark Identifier	90%
New Shark Identifier	96%
Old Shark Genus Classification*	70%
New Shark Genus Classification	72%
Old Shark Species Classification*	70%
New Shark Species Classification (average)	74%

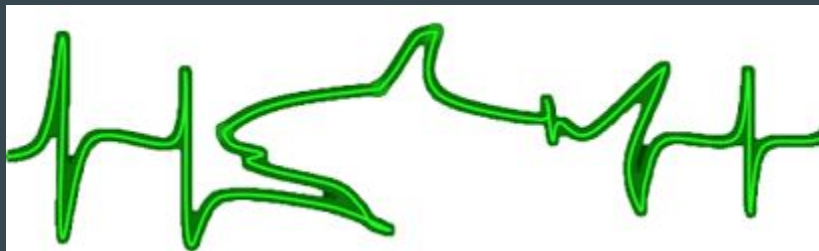
*The old genus and species classifiers were used in tandem, and should not be directly compared to.

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

References

<http://sp2.cs.vt.edu/> (sharkpulse website)

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