



# The Nature Conservancy Fisheries Monitoring:

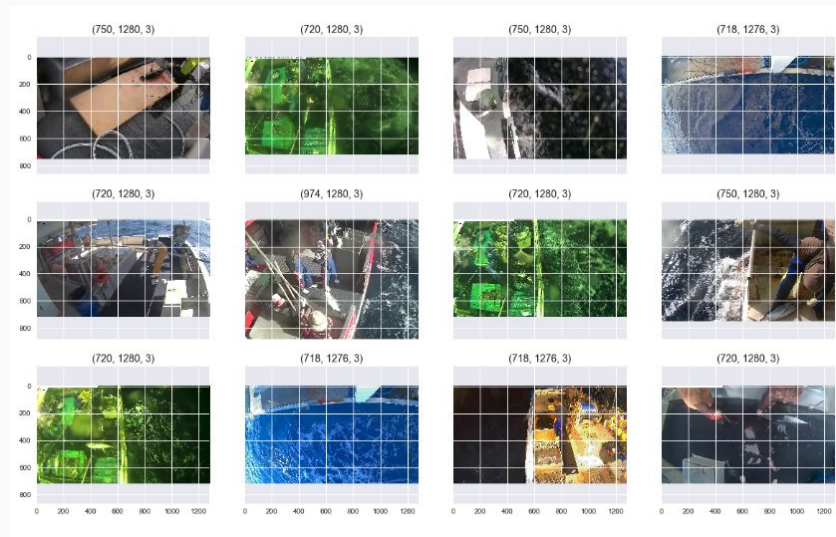
Supporting Automated Fish Classification to Help Maintain  
Ocean Biodiversity

# The problem

- **Goal:** Detect and categorize fish species based on images.
  - **Data source:** The Nature Conservancy
  - **Target categories:** Albacore tuna, Bigeye tuna, Yellowfin tuna, Mahi Mahi, Opah, Sharks, Other (meaning that there are fish present but not in the above categories), and No Fish (meaning that no fish is in the picture)
-

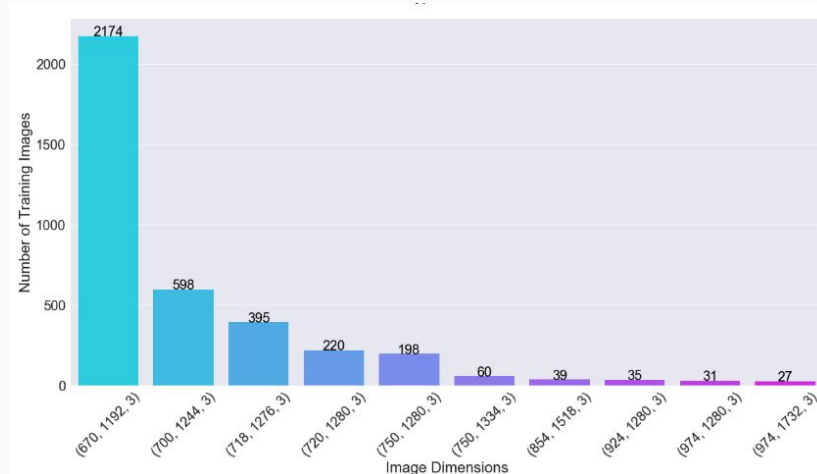
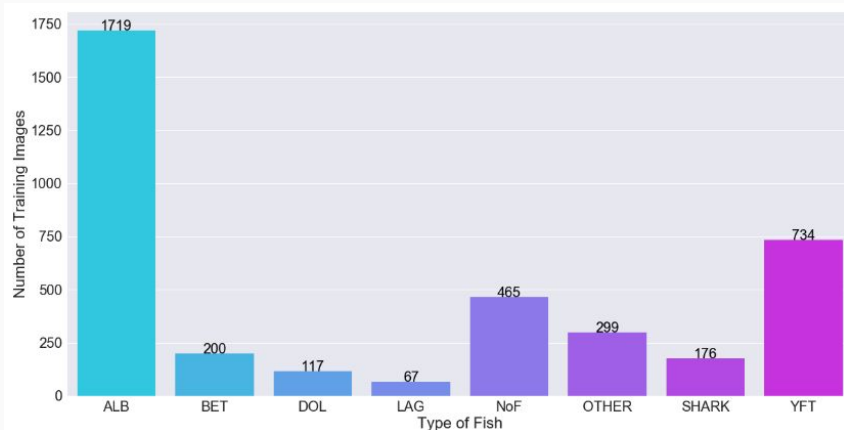
# Exploratory Data Analysis

- Sample Images with Pixel sizes
- Color images (RGB) with pixels and channels as features



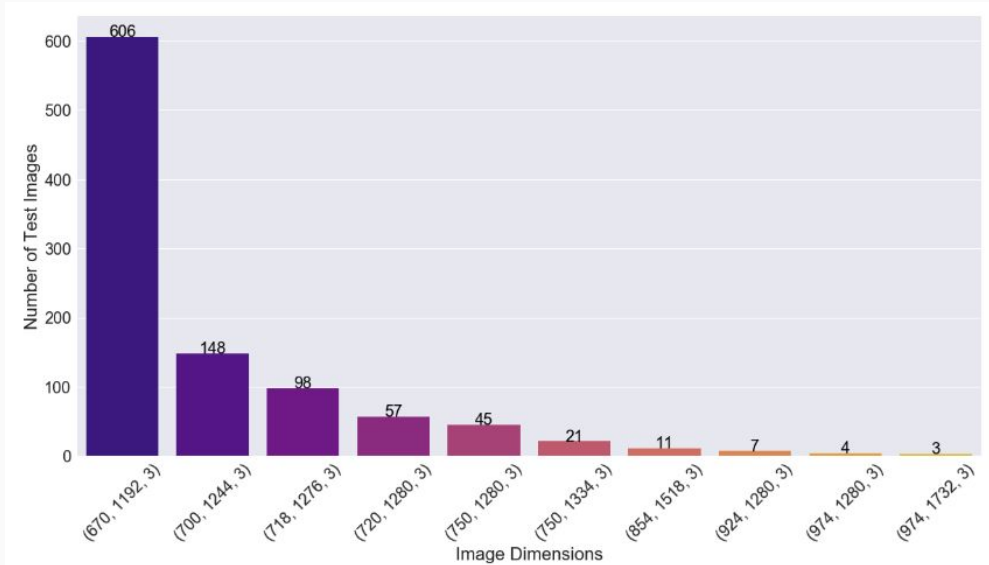
# Training data set

- 3777 Training images with various dimensions and types of fish



# Test data set

- 1000 Test images with various dimensions



# Data Preprocessing

- OpenCV used for reading image files
- CNNs require all image sizes and aspect ratio to be constant over all input images
- Through trial and error, we decided 70x124 (row x col) yielded the best results based on accuracy
- One-hot encoding used based on the categorical nature of our dataset
- Convert data from int8 format into float32
- Dimensionality reduction used for our grey-scale model

# Baseline Results

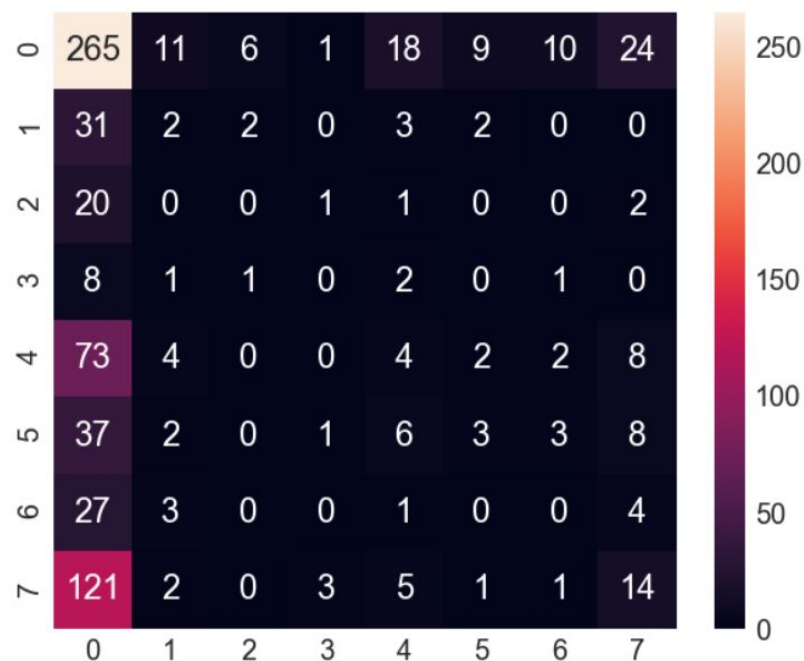
Baseline Accuracy: 0.1204

Baseline Log Loss: 15.07955286364076

##-##-##-##-##-##-##-##-##-##-##-##-##-##-##

Classification Report for Baseline Accuracy

	precision	recall	f1-score	support
0	0.43	0.42	0.42	344
1	0.04	0.05	0.04	40
2	0.00	0.00	0.00	24
3	0.00	0.00	0.00	13
4	0.14	0.14	0.14	93
5	0.10	0.07	0.08	60
6	0.00	0.00	0.00	35
7	0.23	0.24	0.24	147
micro avg	0.27	0.26	0.27	756
macro avg	0.12	0.11	0.12	756
weighted avg	0.27	0.26	0.27	756
samples avg	0.19	0.26	0.21	756



# Training Model 1: RGB

Layer (type)	Output Shape	Param #
cropping2d_1 (Cropping2D)	(None, 66, 120, 3)	0
activation_3 (Activation)	(None, 66, 120, 3)	0
activation_4 (Activation)	(None, 66, 120, 3)	0
conv2d_4 (Conv2D)	(None, 66, 120, 32)	896
activation_5 (Activation)	(None, 66, 120, 32)	0
conv2d_5 (Conv2D)	(None, 66, 120, 64)	18496
conv2d_6 (Conv2D)	(None, 66, 120, 128)	73856
max_pooling2d_2 (MaxPooling2D)	(None, 33, 60, 128)	0
dropout_2 (Dropout)	(None, 33, 60, 128)	0
conv2d_7 (Conv2D)	(None, 33, 60, 256)	295168
max_pooling2d_3 (MaxPooling2D)	(None, 16, 30, 256)	0
dropout_3 (Dropout)	(None, 16, 30, 256)	0
flatten_1 (Flatten)	(None, 122880)	0
dense_2 (Dense)	(None, 256)	31457536
dense_3 (Dense)	(None, 8)	2056
Total params: 31,848,008		
Trainable params: 31,848,008		
Non-trainable params: 0		

# Training Model 2: Grayscale

Layer (type)	Output Shape	Param #
cropping2d (Cropping2D)	(None, 66, 120, 1)	0
activation (Activation)	(None, 66, 120, 1)	0
activation_1 (Activation)	(None, 66, 120, 1)	0
conv2d (Conv2D)	(None, 66, 120, 32)	320
activation_2 (Activation)	(None, 66, 120, 32)	0
conv2d_1 (Conv2D)	(None, 66, 120, 64)	18496
conv2d_2 (Conv2D)	(None, 66, 120, 128)	73856
max_pooling2d (MaxPooling2D)	(None, 33, 60, 128)	0
dropout (Dropout)	(None, 33, 60, 128)	0
conv2d_3 (Conv2D)	(None, 33, 60, 256)	295168
max_pooling2d_1 (MaxPooling2D)	(None, 16, 30, 256)	0
dropout_1 (Dropout)	(None, 16, 30, 256)	0
flatten (Flatten)	(None, 122880)	0
dense (Dense)	(None, 256)	31457536
dense_1 (Dense)	(None, 8)	2056
Total params: 31,847,432		
Trainable params: 31,847,432		
Non-trainable params: 0		



## Testing Model 1: RGB

```
756/756 [=====] - 44s 58ms/step  
Validation Log Loss: 0.2976813446213345
```

## Training Model 2: Grayscale

```
756/756 [=====] - 40s 52ms/step  
Validation Log Loss Grayscale: 0.3333505303601569
```

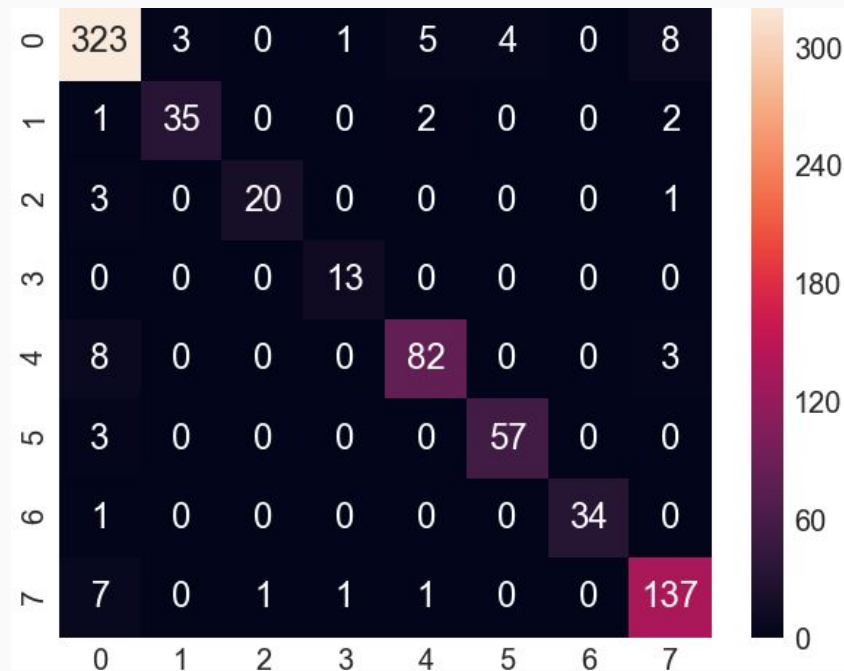
## Conclusions

- There was not a huge difference between the RGB/Grayscale models in terms of log loss, time to train, or overfitting - (RGB had slightly lower validation log loss)
- Trial and error is very important with CNN - lots of settings, and not always intuitive which will work best
- If we had time to try additional improvements, we would use tfrecord to convert files to a faster format and allow for easier training and potentially deeper layering at little computational cost

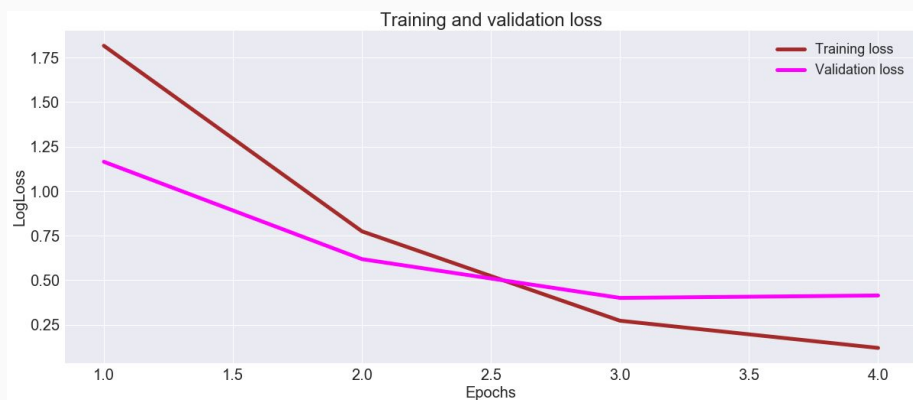
# How accurate are we?

Classification Report for Grayscale Model Accuracy

	precision	recall	f1-score	support
0	0.92	0.96	0.94	344
1	0.92	0.90	0.91	40
2	0.78	0.88	0.82	24
3	1.00	1.00	1.00	13
4	0.96	0.86	0.91	93
5	0.92	0.97	0.94	60
6	1.00	0.94	0.97	35
7	0.93	0.88	0.90	147
micro avg	0.93	0.93	0.93	756
macro avg	0.93	0.92	0.92	756
weighted avg	0.93	0.93	0.93	756

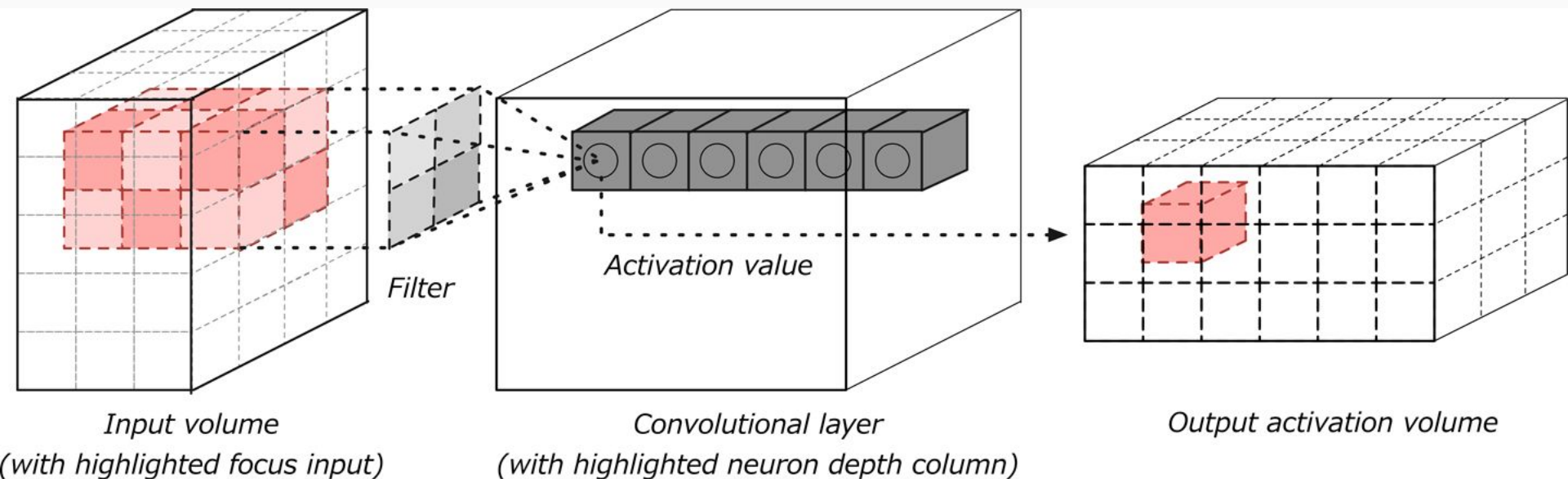


# How accurate are we?



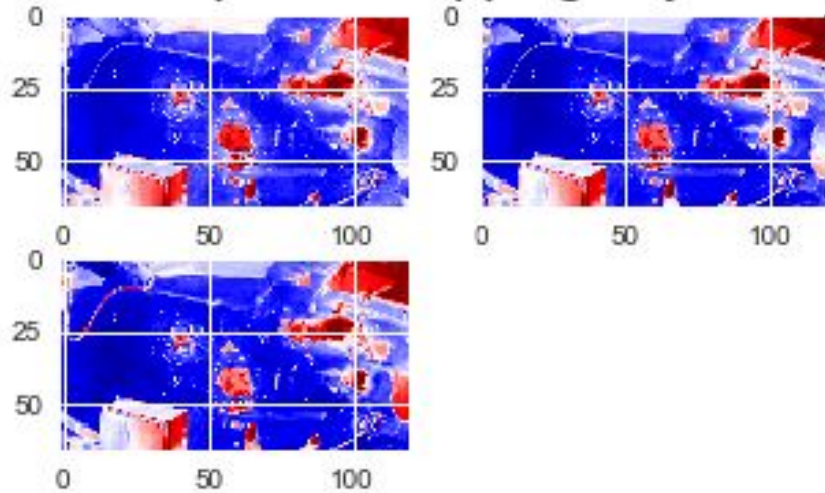
- We visualized our training loss vs. validation loss to help us evaluate the potential for overfitting or underfitting
- We also visualized the accuracy to understand and ensure we are not over fitting, or stopping training too early

# Visualizing the Network: First Convolutional Layer

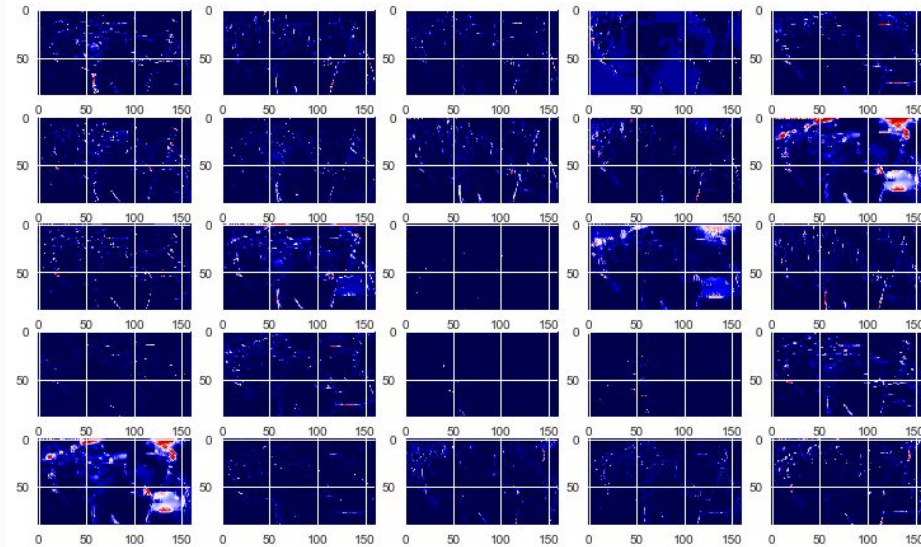


# Visualizing the Network: First Convolutional Layer

Output of Cropping Layer

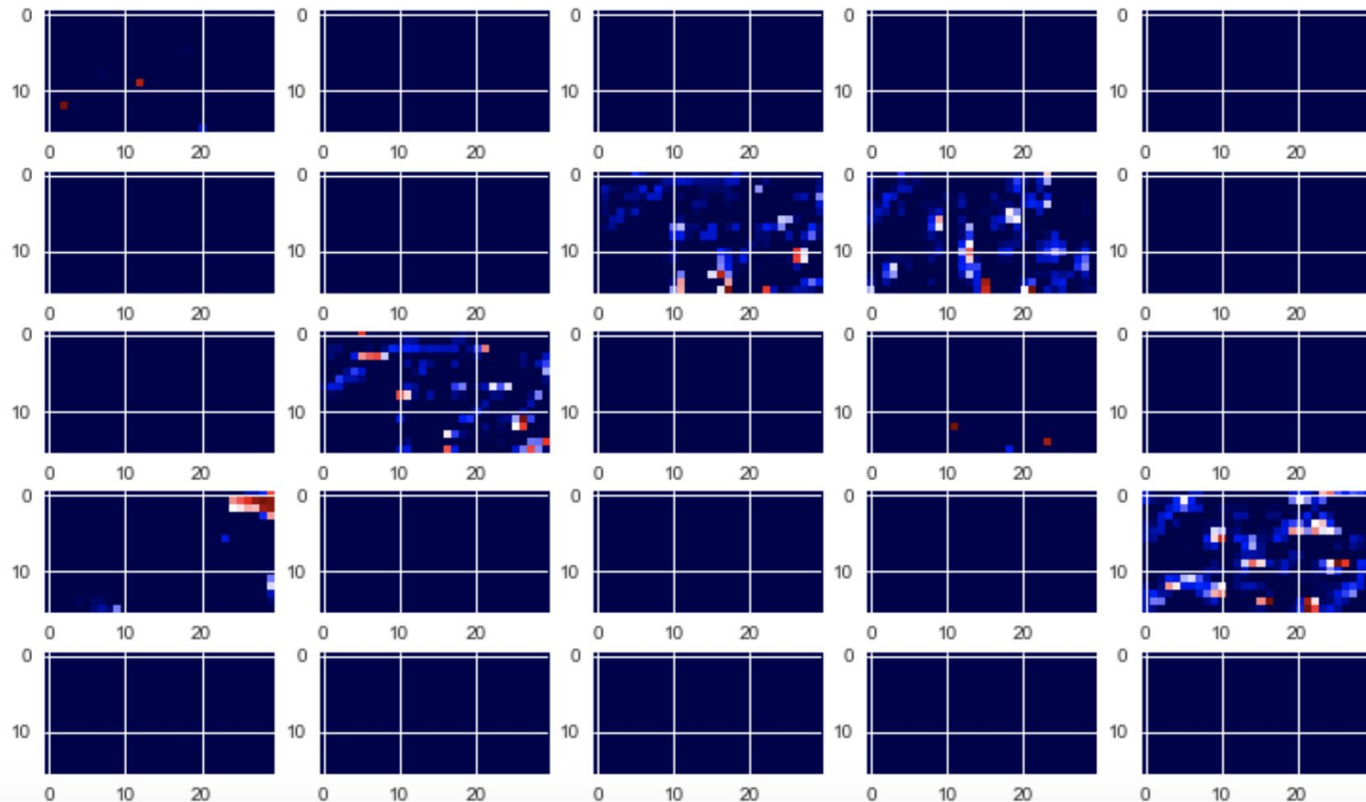


Output of First Convolutional Layer



# Visualizing the Network: Last Max Pooling Layer

Output of Last Max Pooling Layer



# Computer Vision helping to save the oceans

