Classifying images of stars & galaxy and asteroids using Convolutional Neural Networks

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Lawrence Livermore National Laboratory

Team 4 Introduction

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Outline

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Background

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Major Challenge

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Introduction of Machine Learning

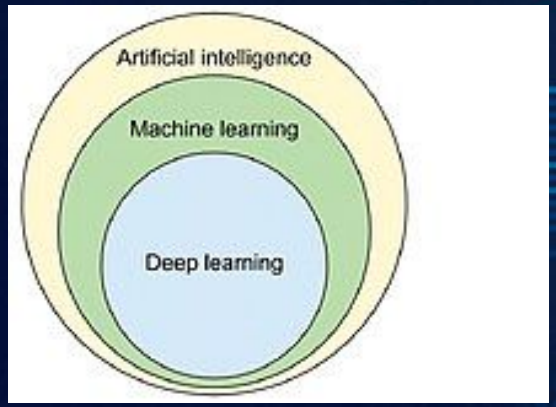


Fig.1

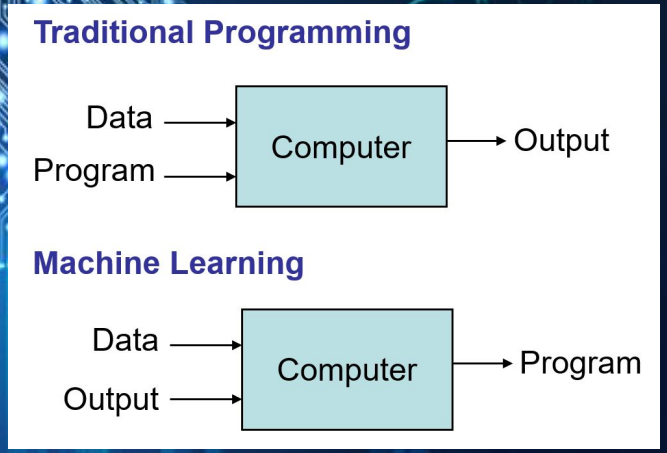


Fig.2

	Supervised Learning	Unsupervised Learning
Discrete	classification or categorization	clustering
Continuous	regression	dimensionality reduction

Fig.3

Supervised Learning

- Apply a prediction function to a feature representation of the image to get the desired output:

f( ) = “fruit”

f( ) = “animal”

$y = f(\mathbf{x})$

output — prediction function — Image feature

Fig.4

Unsupervised Learning

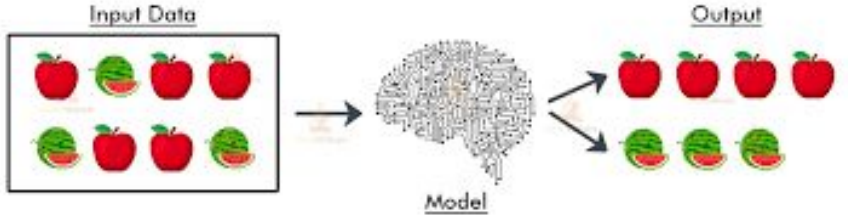
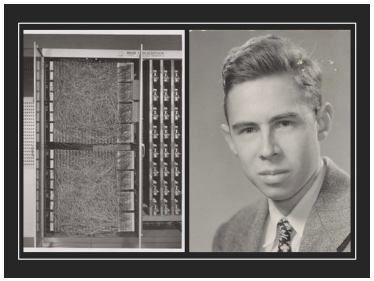


Fig.5

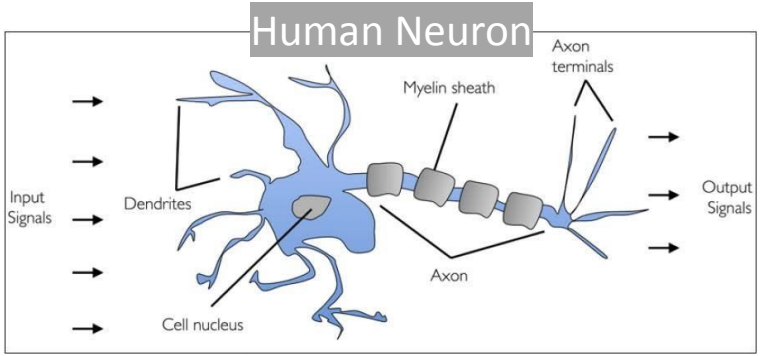
Neural Networks

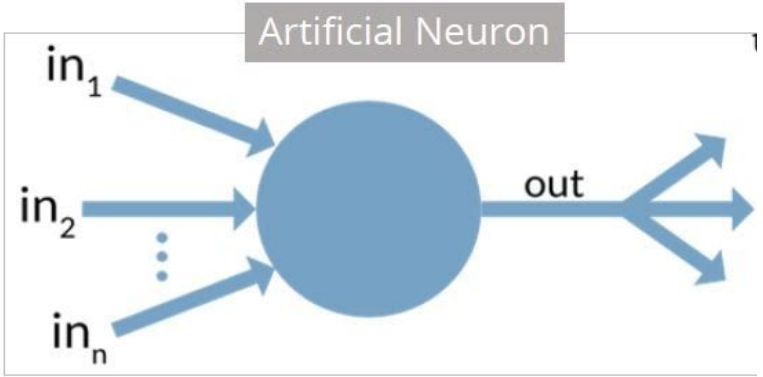
- ➔ Mimic the operations of a human brain to recognize relationships between vast amounts of data
- ➔ Neuron - Basic computation unit [input - process - output]
- ➔ Activation Function - Defines the output for an input
  - ◆ Linear
  - ◆ ReLU
  - ◆ Heaviside
- ➔ Perceptron - Simplest type of Neural Network - Classifier



Left: **Mark I Perceptron machine -** Image Recognition
Right: **Dr. Frank Rosenblatt**
PhD Experimental Psychology, Cornell, 1956

Source:
https://machinelearningknowledge.ai/timeline/perceptron-neuron-that-can-learn/

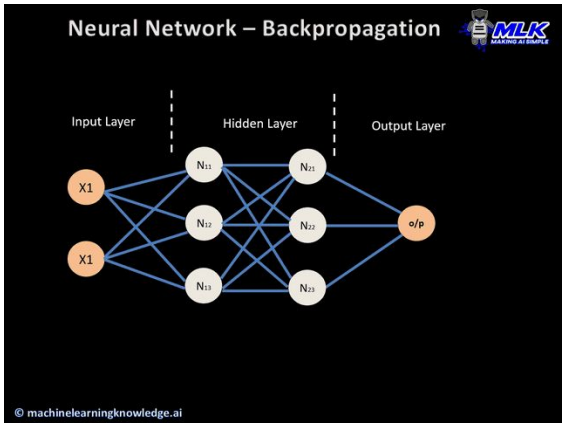




Source: https://www.simplilearn.com/tutorials/deep-learning-tutorial/perceptron

Neural Networks

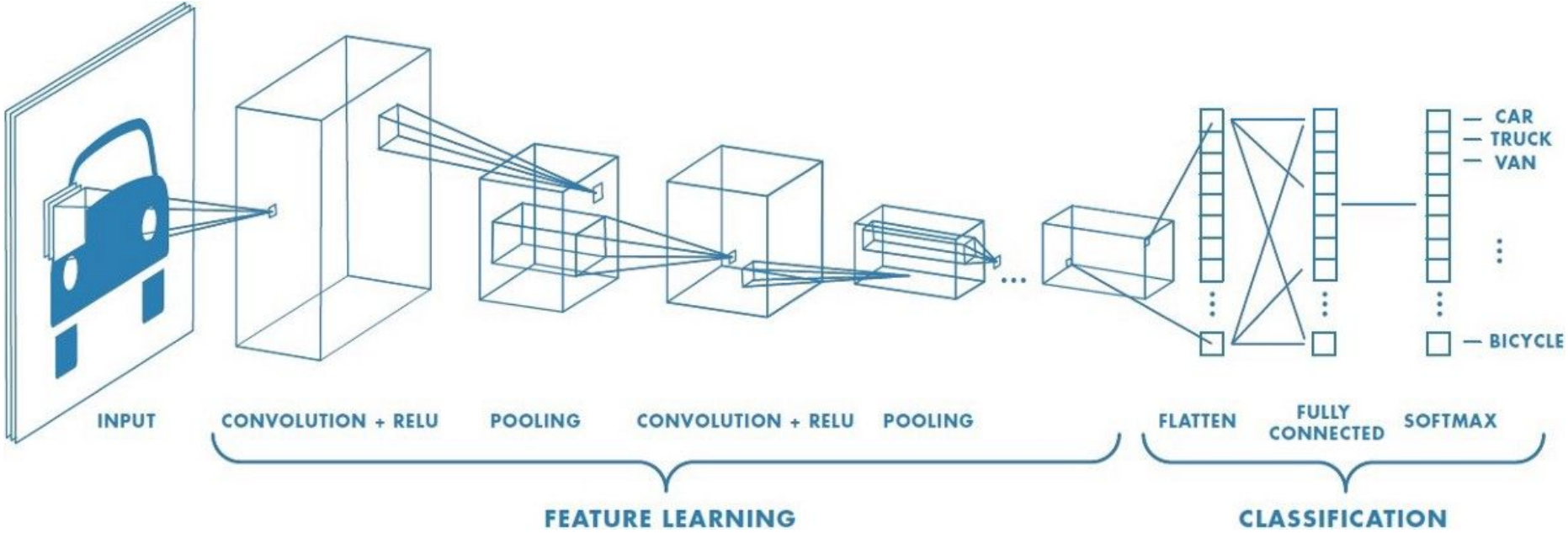
- ➔ Multiple perceptron layers (MLPs) - Welcomes non-linearity
- ➔ Learning with Forward and Backward propagations
- ➔ Forward Pass - Make predictions
- ➔ Backward Pass - Adjust weights with observed loss



Source: https://machinelearningknowledge.ai/animated-explanation-of-feed-forward-neural-network-architecture/

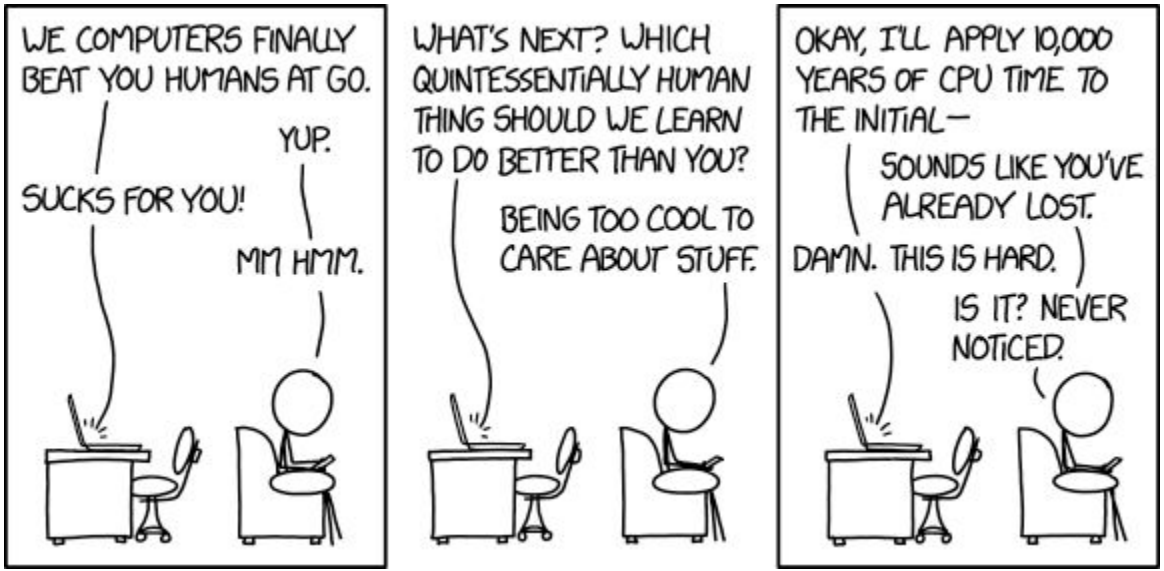
Source: https://xkcd.com/1838/

Convolutional Neural Network



Source: https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

Cannot Model Everything



Source: https://xkcd.com/1875/

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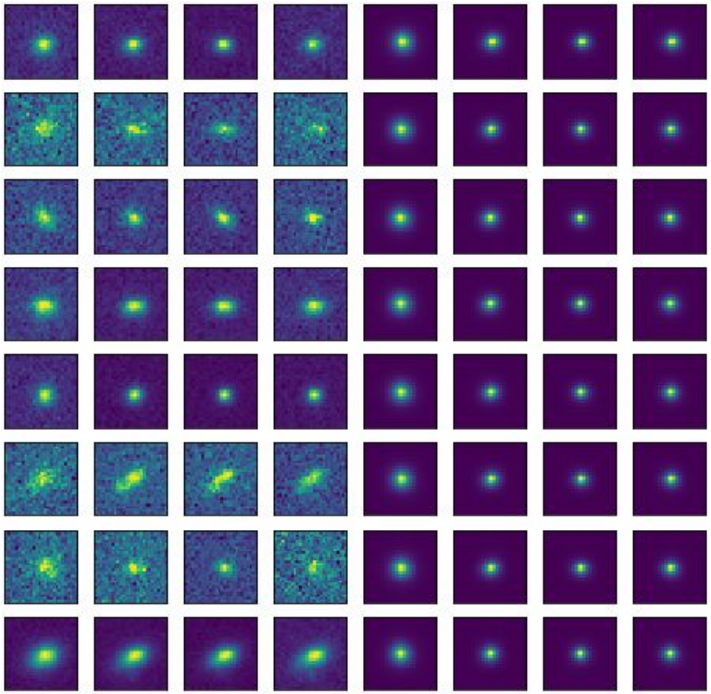
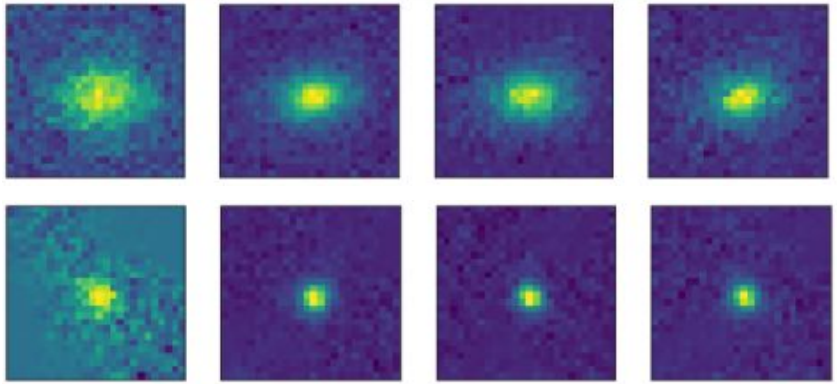
Mini Challenge - Intro

Star vs. Galaxy Classification



- ~ 34,000 images
- 8 channels per image
- First 4 channels seem to be more indicative and rich.
- Last 4 channels might have some hidden features that a model could detect



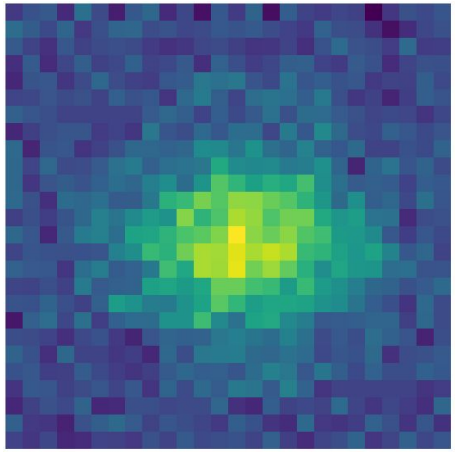
Class = 0
galaxy

Class = 1
star

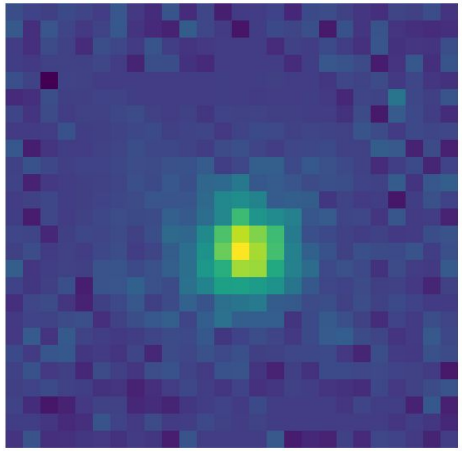
Mini Challenge - Intro

Aim

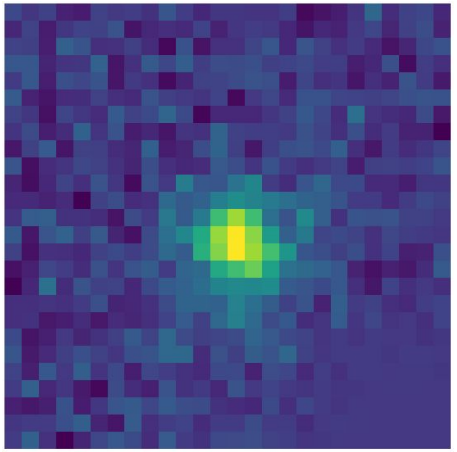
Differentiate between star and galaxy 26x26 images using Deep Learning Models.



Class = ???

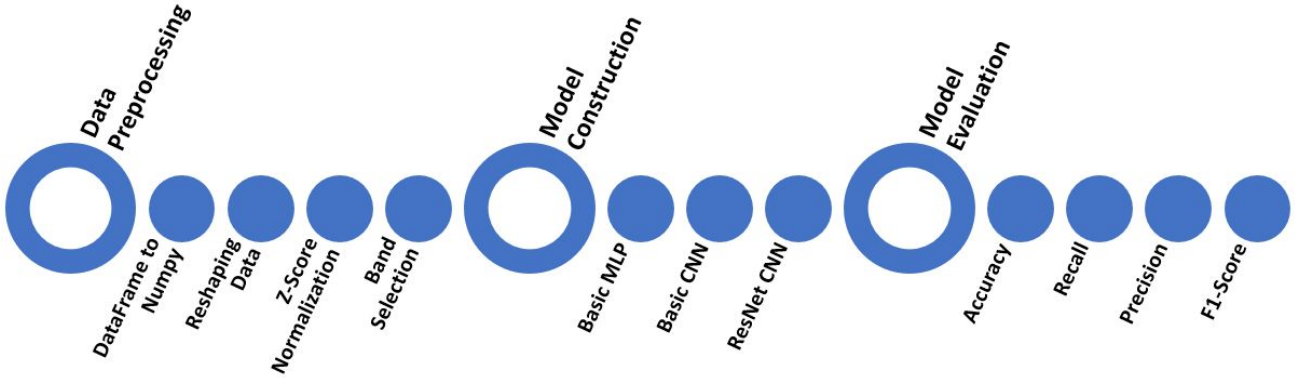


Class = ???



Class = ???

Mini Challenge - Methodology



Model Construction

- We decided on three different models, to see which one would perform the best on this data set.

Data Preprocessing

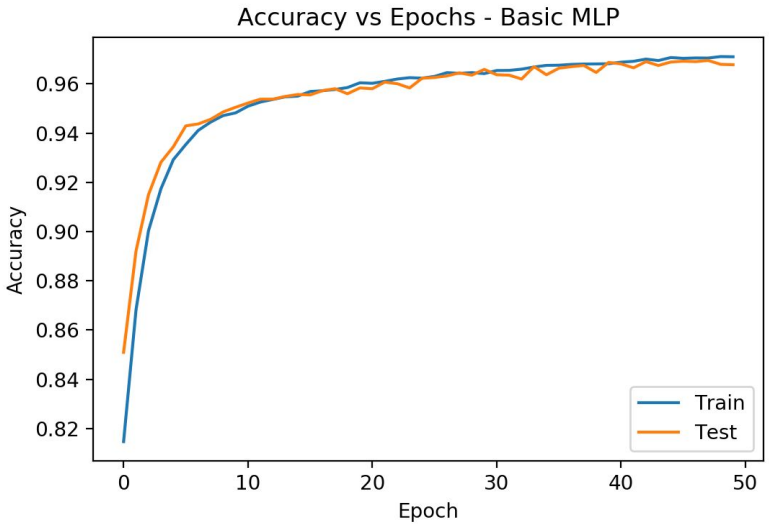
- We had to convert Pandas DataFrame to several Numpy arrays
  - Reshaped data to (26, 26)
- Normalized using z-score
- Selected all 8 bands

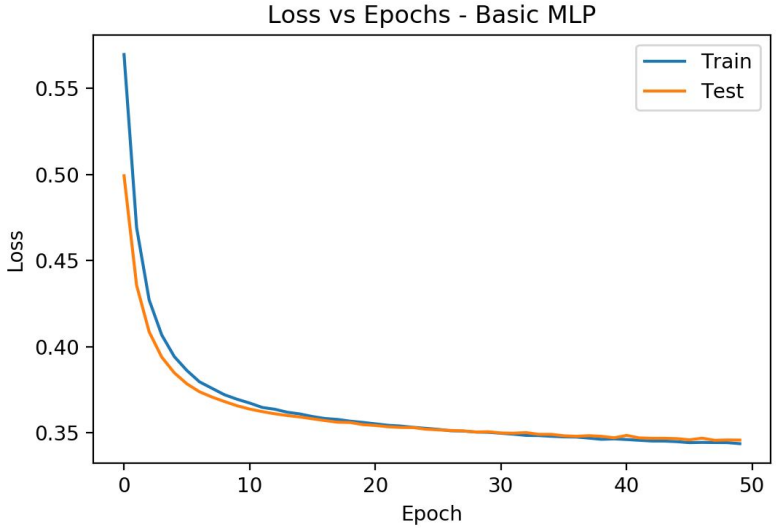
Model Evaluation

- Accuracy, Precision, and Recall scores (both micro and macro)
- F1 Score and classification reports for every model

Mini Challenge - Results

Accuracy & Loss vs Epoches - Multi-Layer Perceptron Model

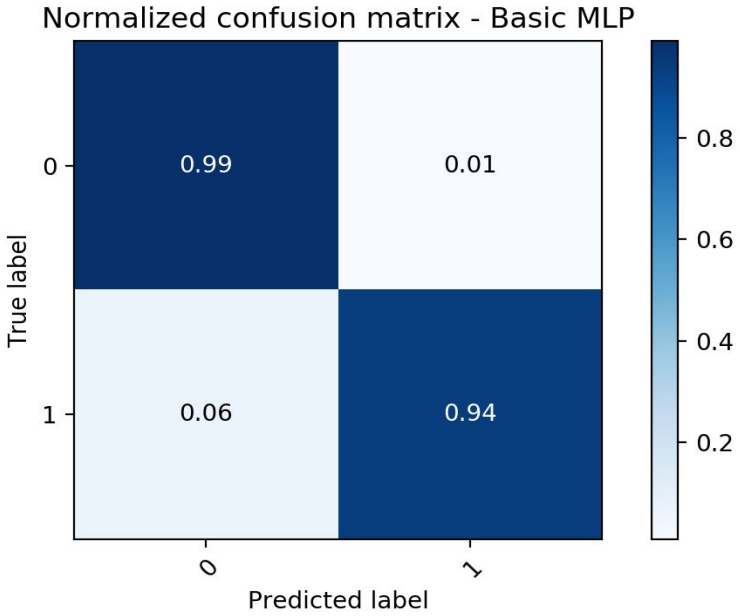


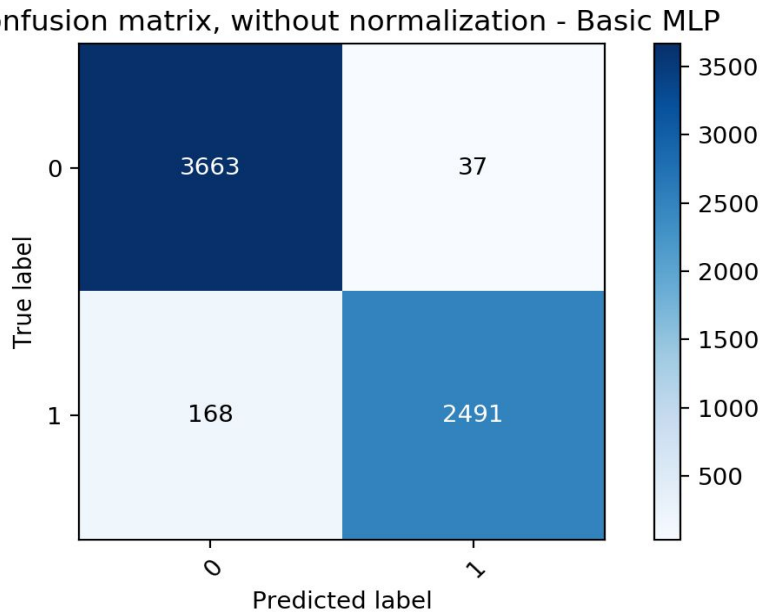


Total training time: 340.37s (5.67m)
Learning rate: 0.01
Batch size: 64

Mini Challenge - Results

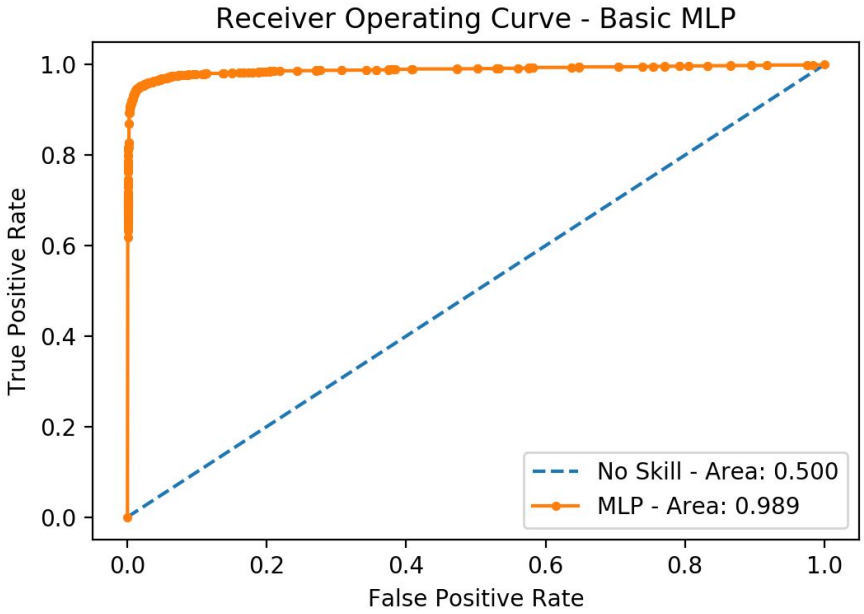
Confusion Matrix - Multi-Layer Perceptron Model

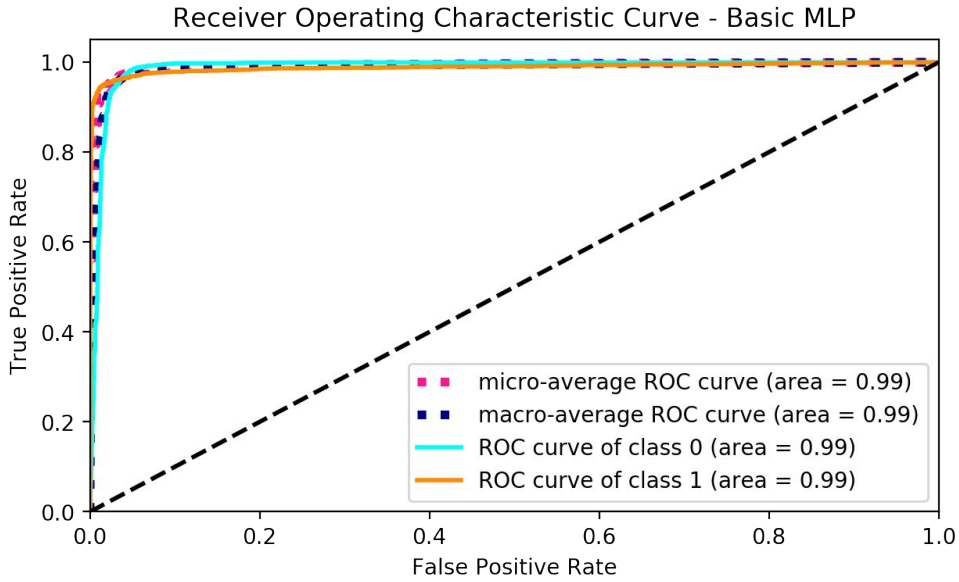




Mini Challenge - Results

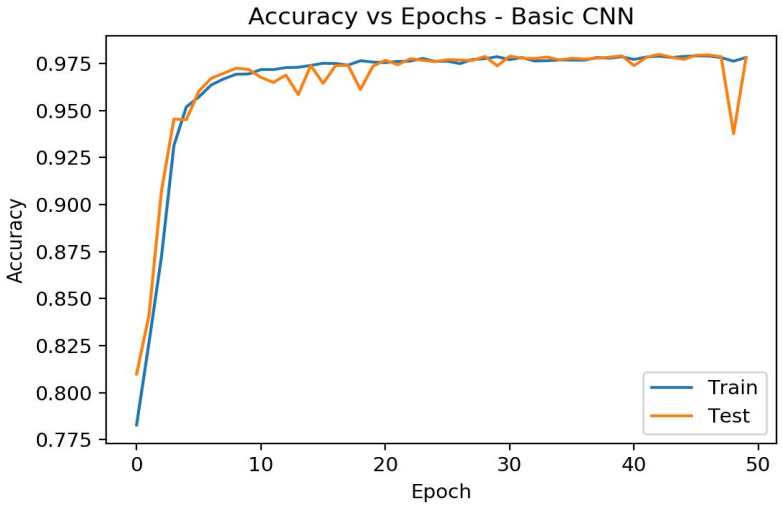
ROC Curve - Multi-Layer Perceptron Model

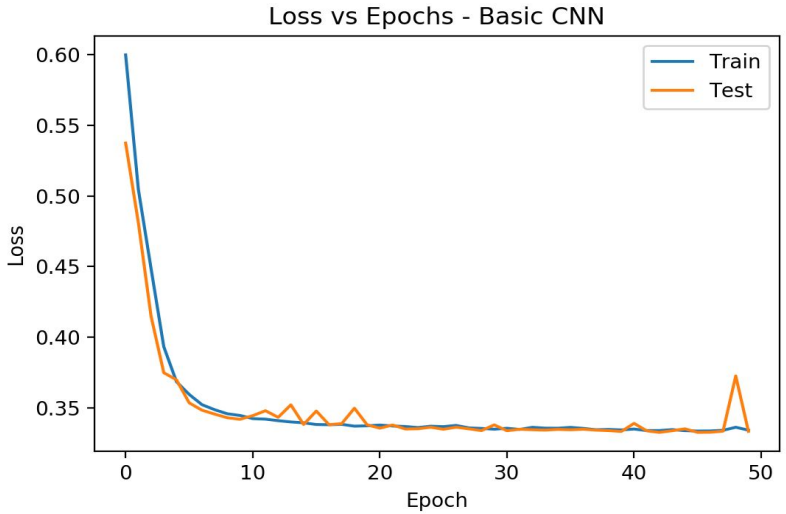




Mini Challenge - Results

Accuracy & Loss vs Epoches - Convolutional Neural Network

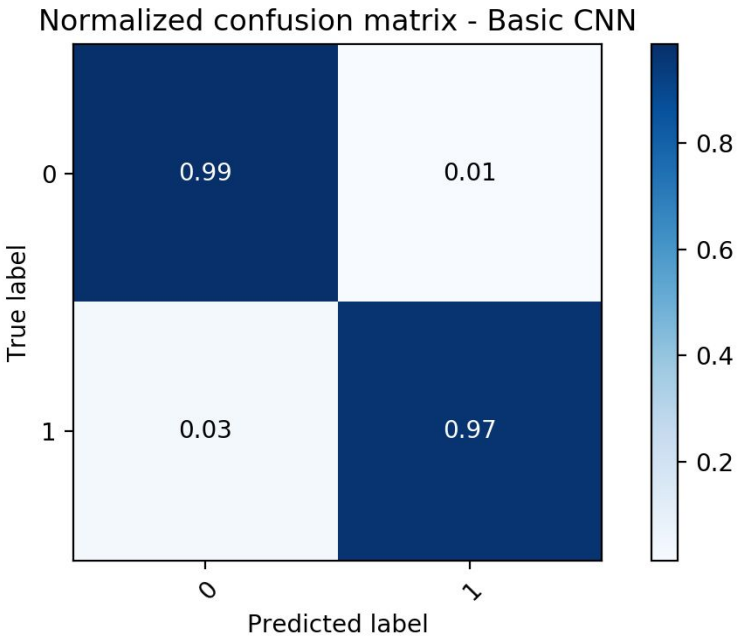


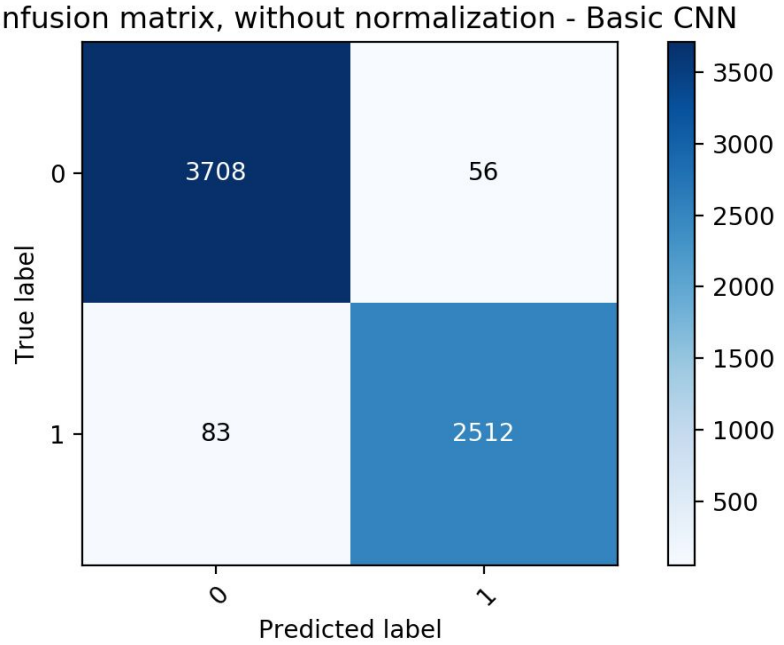


Total training time: 820.72s (13.68m)
Learning rate: 0.01
Batch size: 64

Mini Challenge - Results

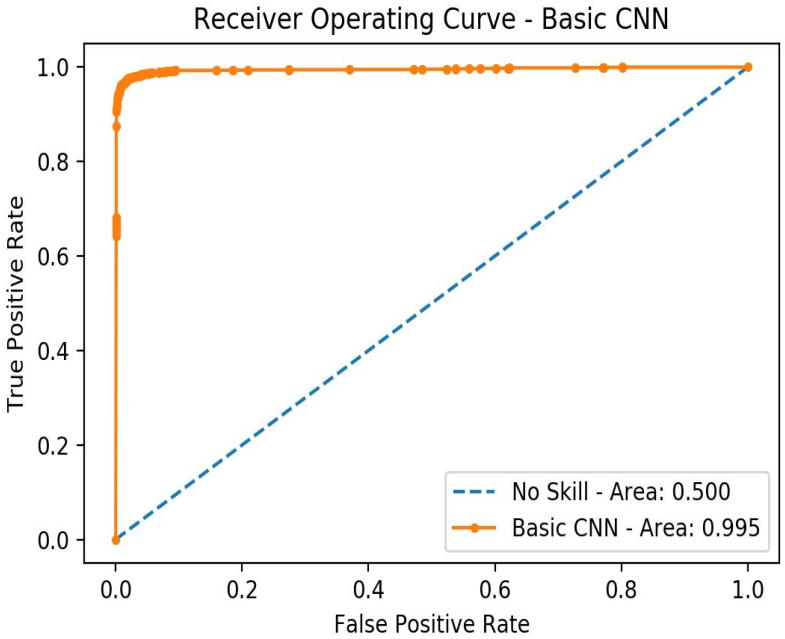
Confusion Matrix - Convolutional Neural Networks

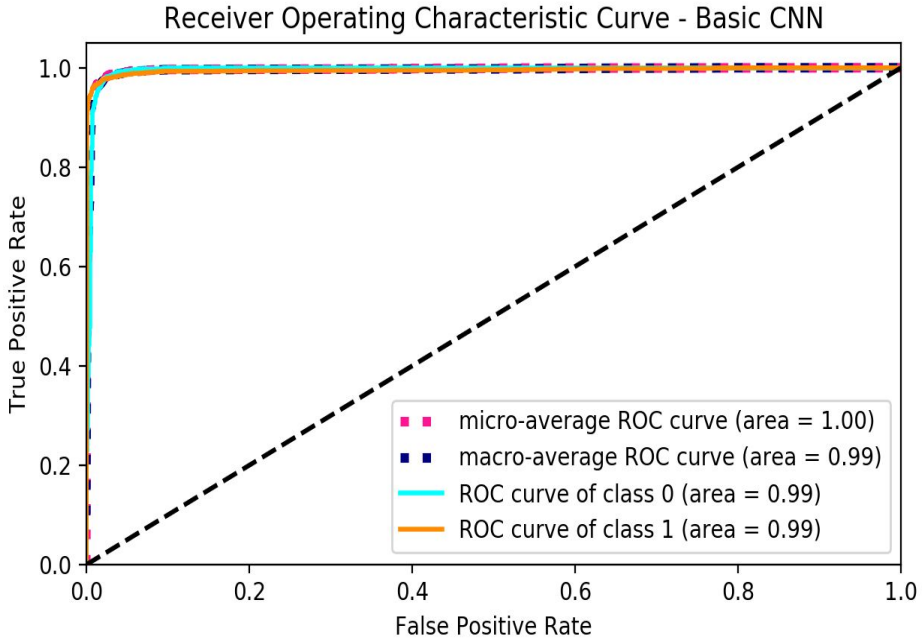




Mini Challenge - Results

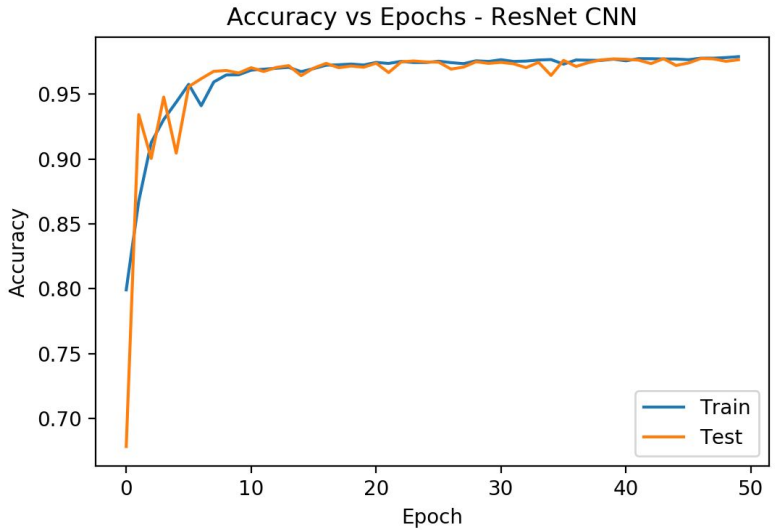
Confusion Matrix - Convolutional Neural Networks

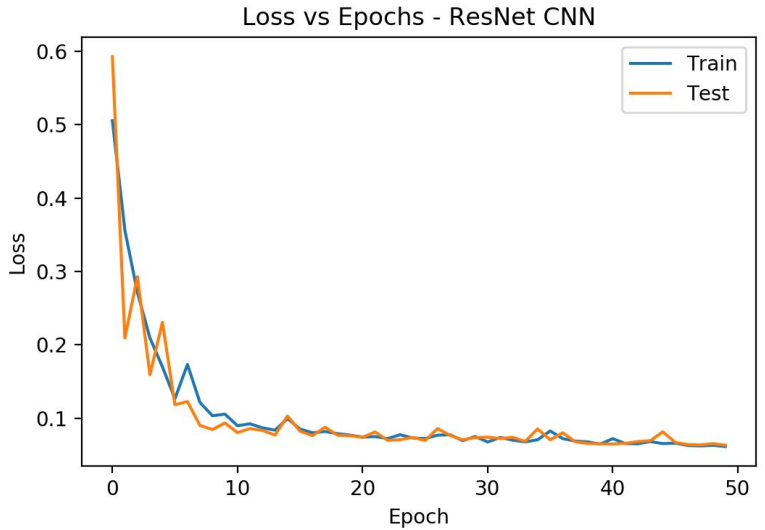




Mini Challenge - Results

Accuracy & Loss vs Epoches - ResNet CNN

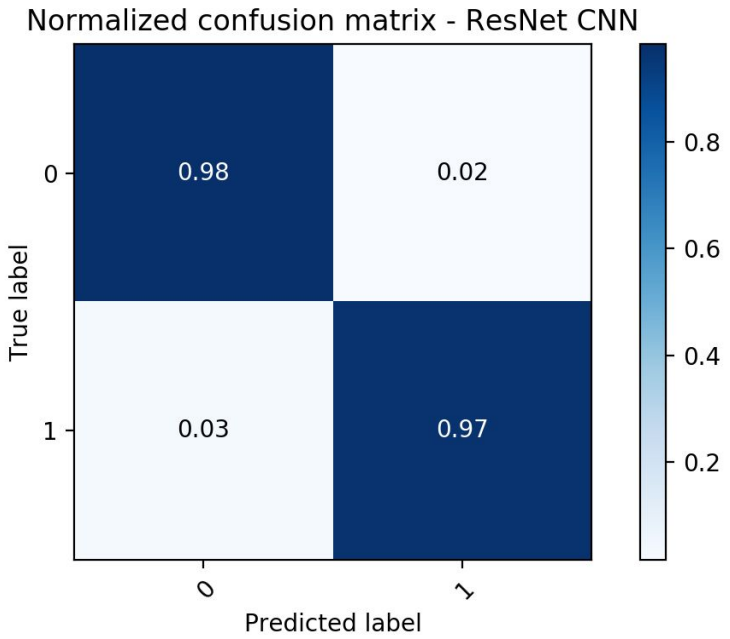


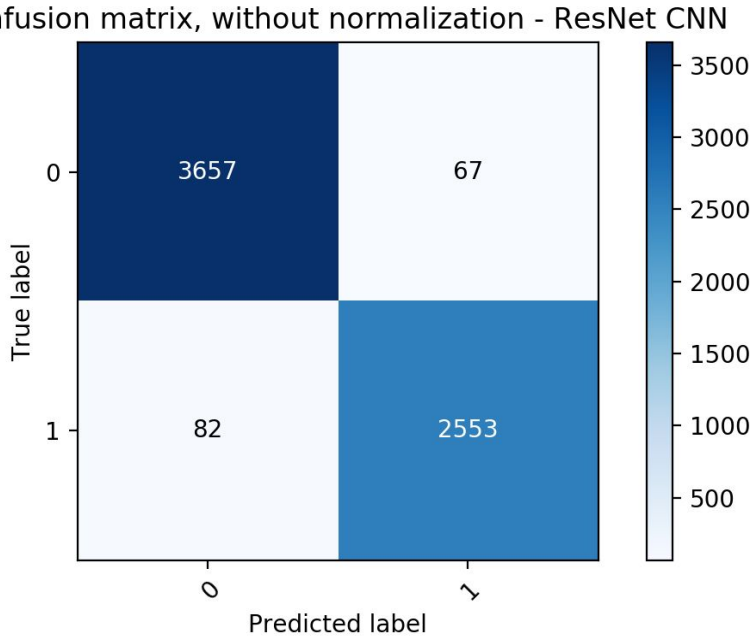


Total training time: 1193.01s (19.88m)
Learning rate: 0.01
Batch size: 64

Mini Challenge - Results

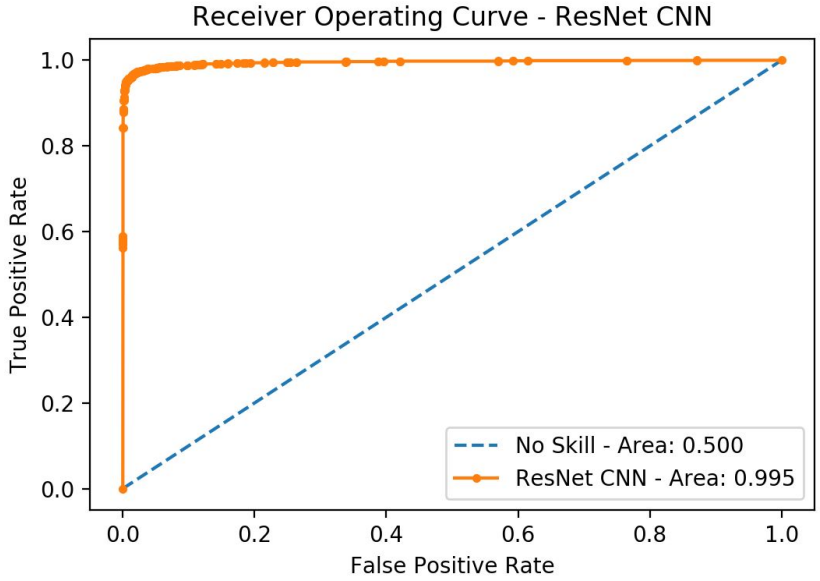
Confusion Matrix - ResNet CNN

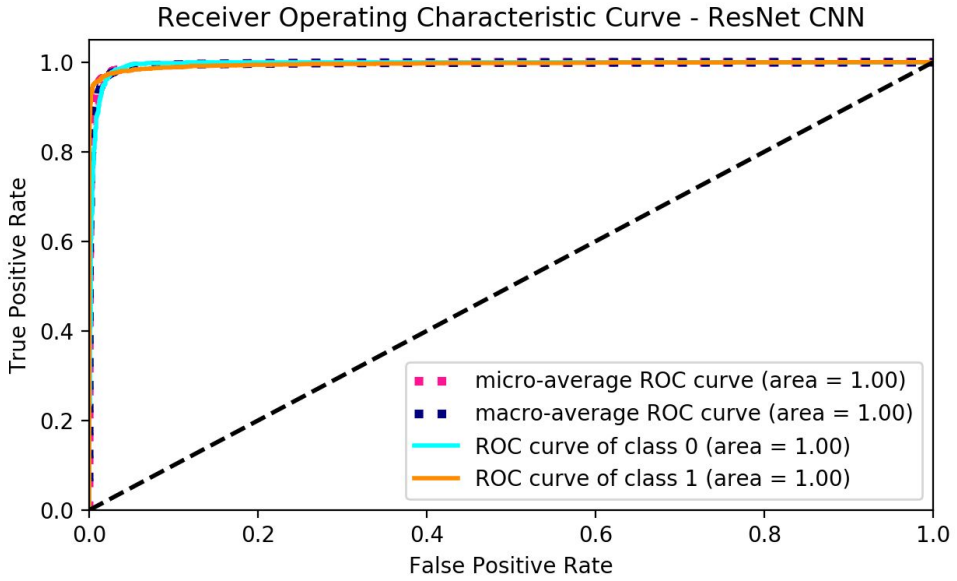




Mini Challenge - Results

Confusion Matrix - ResNet CNN





Mini Challenge - Results

Overall Model Metrics

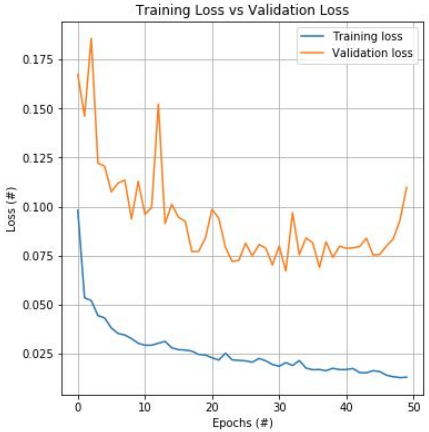
Multi-Layer Perceptron				Basic Convolutional Neural Network				ResNet Convolutional Neural Network			
Class Label	Precision (%)	Recall (%)	F1-Score (%)	Class Label	Precision (%)	Recall (%)	F1-Score (%)	Class Label	Precision (%)	Recall (%)	F1-Score (%)
galaxy	95.61	99.00	97.28	galaxy	97.81	98.51	98.16	galaxy	97.82	98.24	98.03
star	98.54	93.68	96.05	star	97.82	96.80	97.31	star	97.45	96.85	97.15
Micro avg (%)	96.78	96.78	96.78	Micro avg (%)	97.81	97.81	97.81	Micro avg (%)	97.67	97.67	97.67
Macro avg (%)	97.08	96.34	96.66	Macro avg (%)	97.81	97.66	97.73	Macro avg (%)	97.64	97.55	97.59
Weighted avg (%)	96.84	96.78	96.76	Weighted avg (%)	97.81	97.81	97.81	Weighted avg (%)	97.67	97.67	97.67

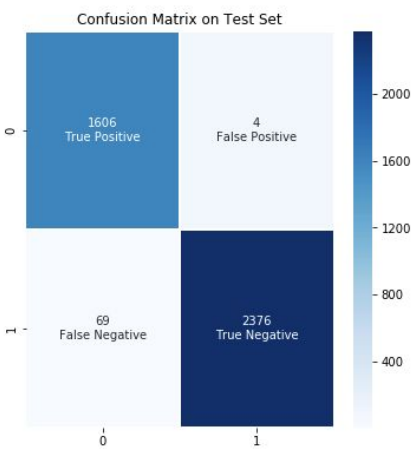
- Overall best performance was achieved by Basic Convolutional Neural Network model.
  - 1) Basic Convolutional Neural Network
  - 2) ResNet Convolutional Neural Network
  - 3) Multi-Layer Perceptron

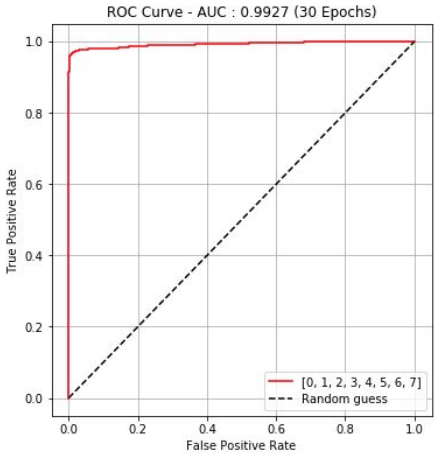
- MLP model achieved impressive recall score for galaxy data

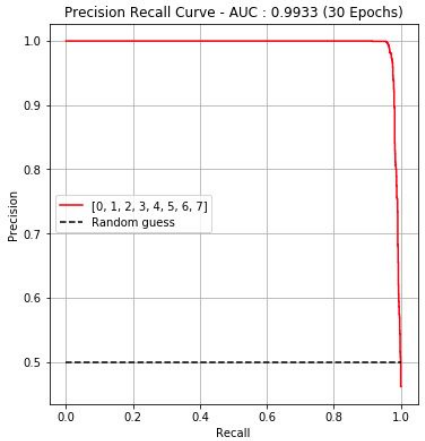
Mini Challenge - Results - Band Configurations

CNN Model - Performance with all bands









Optimal Model Complexity @ 30 epochs

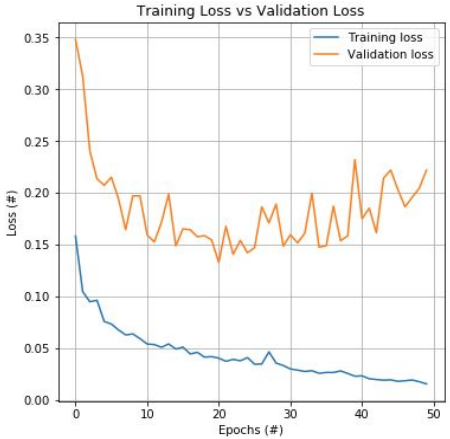
50 epoch train time : 15 mins 29 secs
30 epoch train time : 08 mins 05 secs

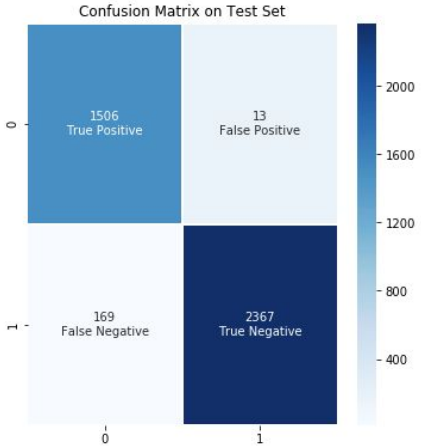
Other Performance Metrics:

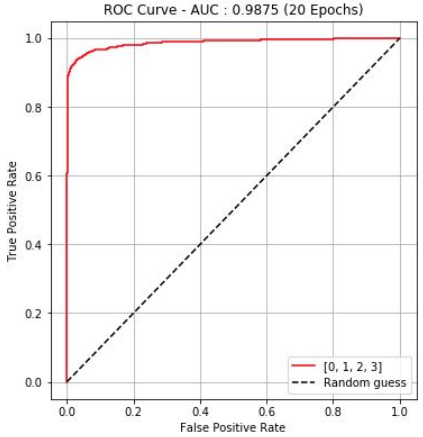
```
('Overall Accuracy : ', 98.19975339087547)
('Star Accuracy : ', 99.83193277310924)
('Galaxy Accuracy : ', 95.88059701492537)
('Precision : ', 95.88059701492537)
('Recall : ', 99.75155279503105)
('F-Measure : ', 97.77777777777777)
```

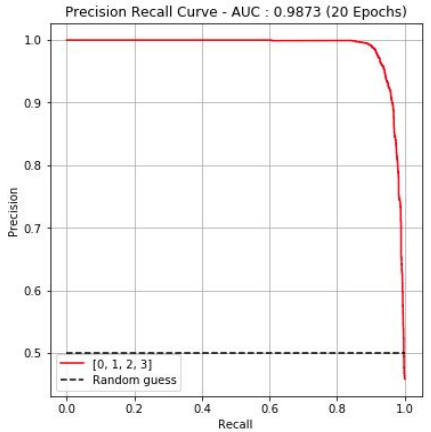
Mini Challenge - Results - Band Configurations

CNN Model - Performance with bands 0 - 3









Optimal Model Complexity @ 20 epochs

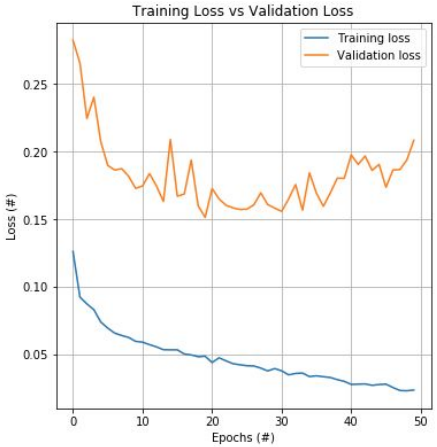
50 epoch train time : 07 mins 55 secs
20 epoch train time : 02 mins 57 secs

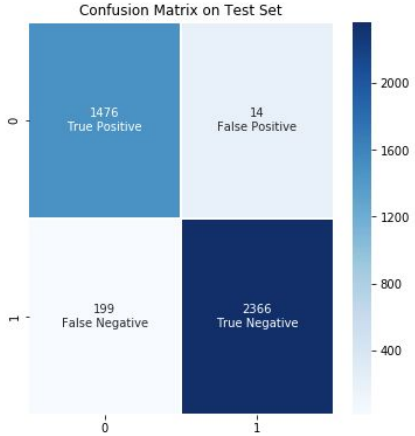
Other Performance Metrics:

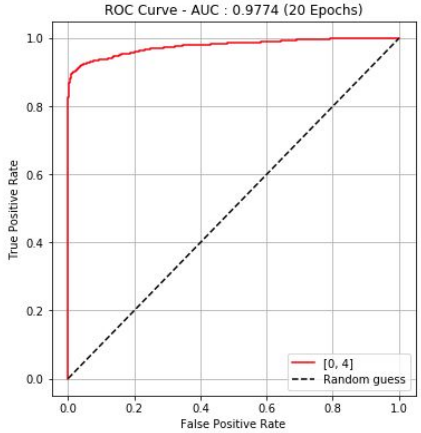
```
('Overall Accuracy : ', 95.51171393341554)
('Star Accuracy : ', 99.45378151260505)
('Galaxy Accuracy : ', 89.91044776119404)
('Precision : ', 89.91044776119404)
('Recall : ', 99.14417379855168)
('F-Measure : ', 94.30181590482154)
```

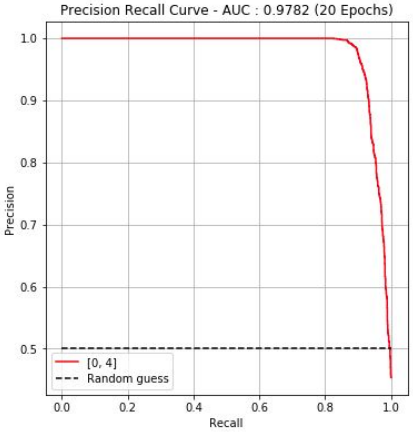
Mini Challenge - Results - Band Configurations

CNN Model - Performance with bands 0, 4









Optimal Model Complexity @ 20 epochs

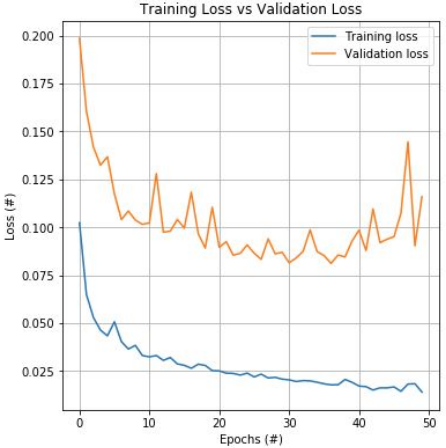
50 epoch train time : 08 mins 41 secs
20 epoch train time : 04 mins 57 secs

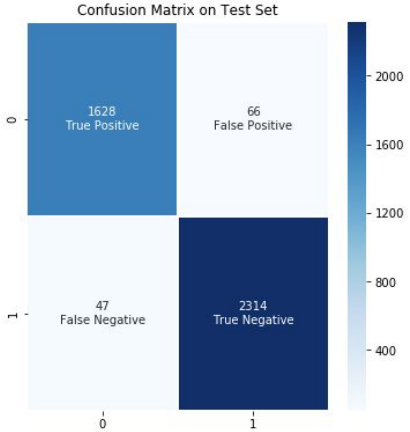
Other Performance Metrics:

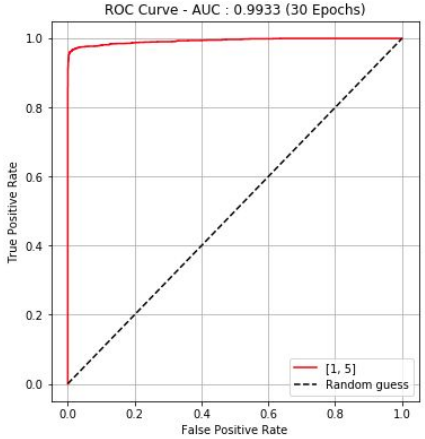
```
('Overall Accuracy : ', 94.74722564734896)
('Star Accuracy : ', 99.41176470588235)
('Galaxy Accuracy : ', 88.11940298507463)
('Precision : ', 88.11940298507463)
('Recall : ', 99.06040268456375)
('F-Measure : ', 93.27014218009478)
```

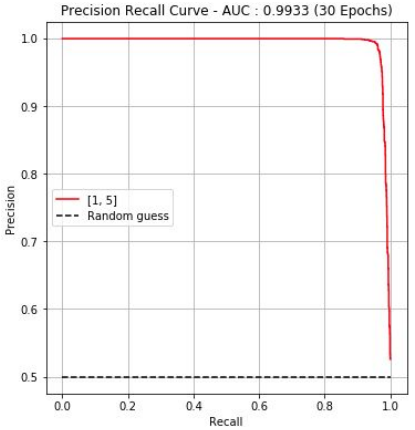
Mini Challenge - Results - Band Configurations

CNN Model - Performance with bands 1, 5









Optimal Model Complexity @ 30 epochs

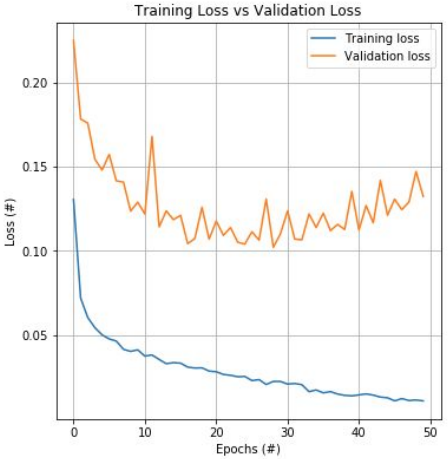
50 epoch train time : 07 mins 18 secs
30 epoch train time : 06 mins 23 secs

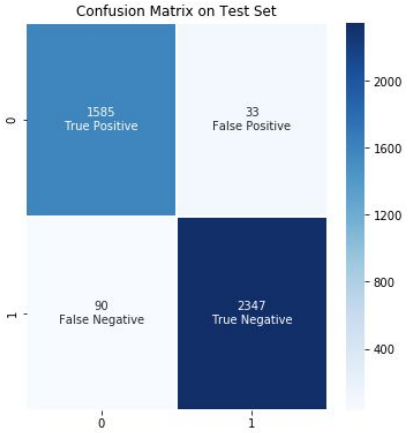
Other Performance Metrics:

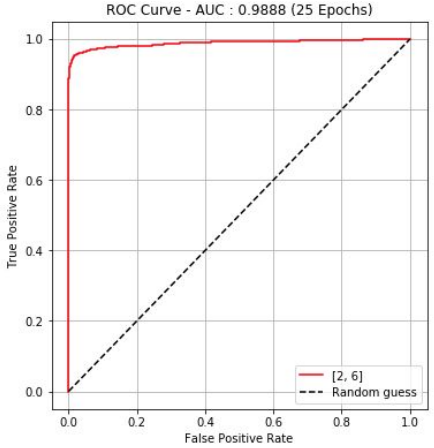
```
('Overall Accuracy : ', 97.21331689272503)
('Star Accuracy : ', 97.22689075630252)
('Galaxy Accuracy : ', 97.19402985074626)
('Precision : ', 97.19402985074626)
('Recall : ', 96.1038961038961)
('F-Measure : ', 96.64588898783022)
```

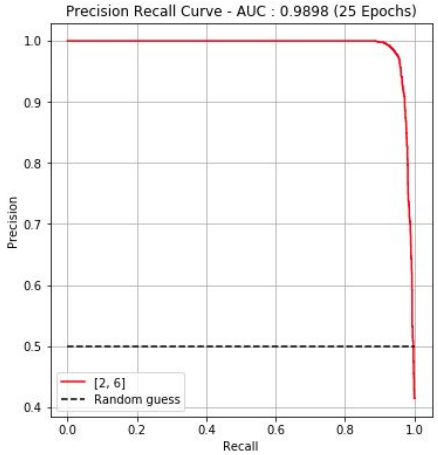
Mini Challenge - Results - Band Configurations

CNN Model - Performance with bands 2, 6









Optimal Model Complexity @ 25 epochs

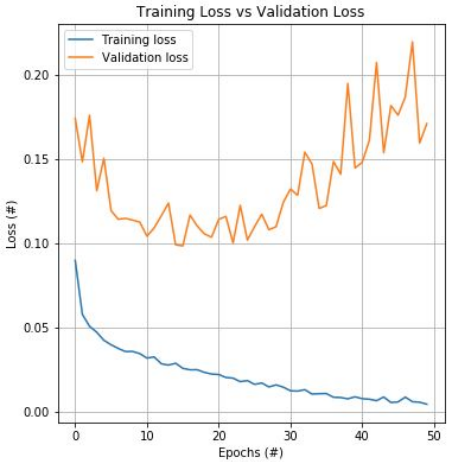
50 epoch train time : 07 mins 36 secs
25 epoch train time : 07 mins 31 secs

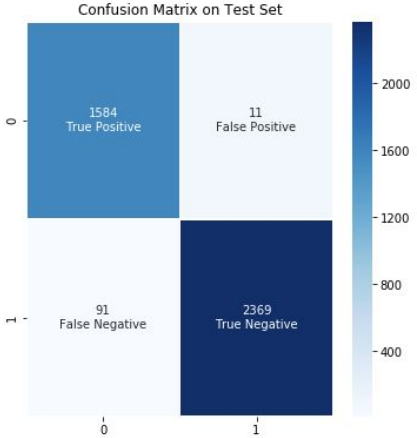
Other Performance Metrics:

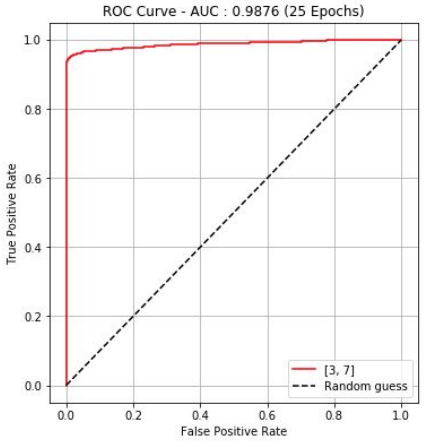
```
('Overall Accuracy : ', 96.96670776818742)
('Star Accuracy : ', 98.61344537815127)
('Galaxy Accuracy : ', 94.6268656716418)
('Precision : ', 94.6268656716418)
('Recall : ', 97.96044499381952)
('F-Measure : ', 96.26480412997266)
```

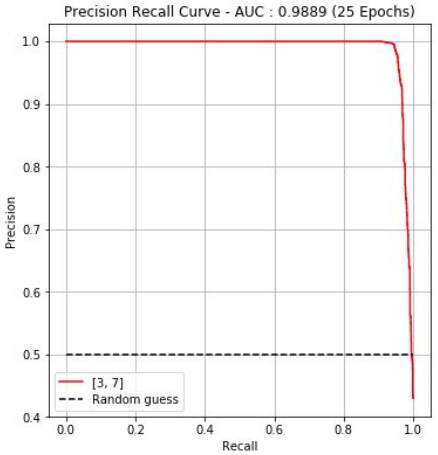
Mini Challenge - Results - Band Configurations

CNN Model - Performance with bands 3, 7









Optimal Model Complexity @ 25 epochs

50 epoch train time : 12 mins 19 secs
25 epoch train time : 07 mins 27 secs

Other Performance Metrics:

```
('Overall Accuracy : ', 97.4845869297164)
('Star Accuracy : ', 99.53781512605042)
('Galaxy Accuracy : ', 94.56716417910448)
('Precision : ', 94.56716417910448)
('Recall : ', 99.3103448275862)
('F-Measure : ', 96.88073394495412)
```

Mini Challenge - Results - Band Configurations

CNN Model - Overall Metrics for Each Configuration

Bands 0-8			
Class Label	Precision (%)	Recall (%)	F1-Score (%)
galaxy	96	100	98
star	100	97	98
Micro avg (%)	98	98	98
Macro avg (%)	98	98	98
Weighted avg (%)	98	98	98

Bands 0-3			
Class Label	Precision (%)	Recall (%)	F1-Score (%)
galaxy	90	99	94
star	99	93	96
Micro avg (%)	96	96	96
Macro avg (%)	95	96	95
Weighted avg (%)	96	96	96

Bands 0, 4			
Class Label	Precision (%)	Recall (%)	F1-Score (%)
galaxy	99	92	96
star	88	99	93
Micro avg (%)	95	95	95
Macro avg (%)	94	96	94
Weighted avg (%)	95	95	95

Bands 1, 5			
Class Label	Precision (%)	Recall (%)	F1-Score (%)
galaxy	97	96	97
star	97	98	98
Micro avg (%)	97	97	97
Macro avg (%)	97	97	97
Weighted avg (%)	97	97	97

Bands 2, 6			
Class Label	Precision (%)	Recall (%)	F1-Score (%)
galaxy	95	98	96
star	99	96	97
Micro avg (%)	97	97	97
Macro avg (%)	97	97	97
Weighted avg (%)	97	97	97

Bands 3, 7			
Class Label	Precision (%)	Recall (%)	F1-Score (%)
galaxy	95	99	97
star	100	96	98
Micro avg (%)	97	97	97
Macro avg (%)	97	98	97
Weighted avg (%)	98	97	97

Outline

Team 4 Introduction

Background

Mini Challenge

Major Challenge

Summary

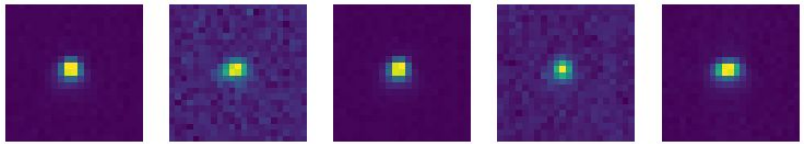
Acknowledgement

Main Challenge - Intro

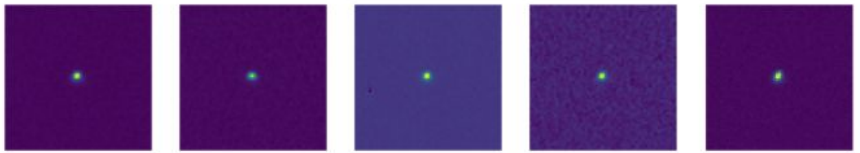
Asteroid Detection

Difference Images (3080x3072 px)

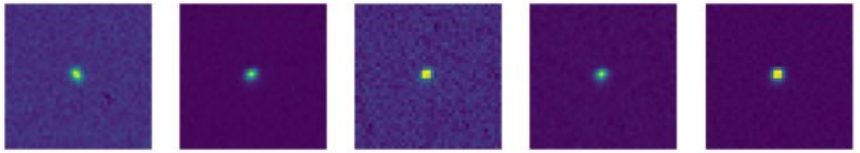
Individual Asteroid Images (26x26)



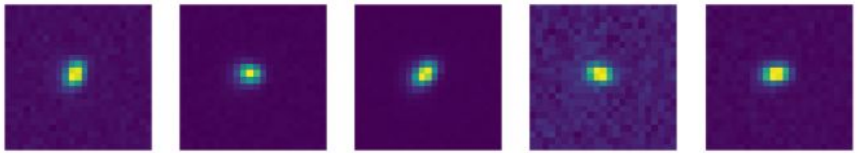
Offset of 20px



Offset of 30px



Offset of 40px



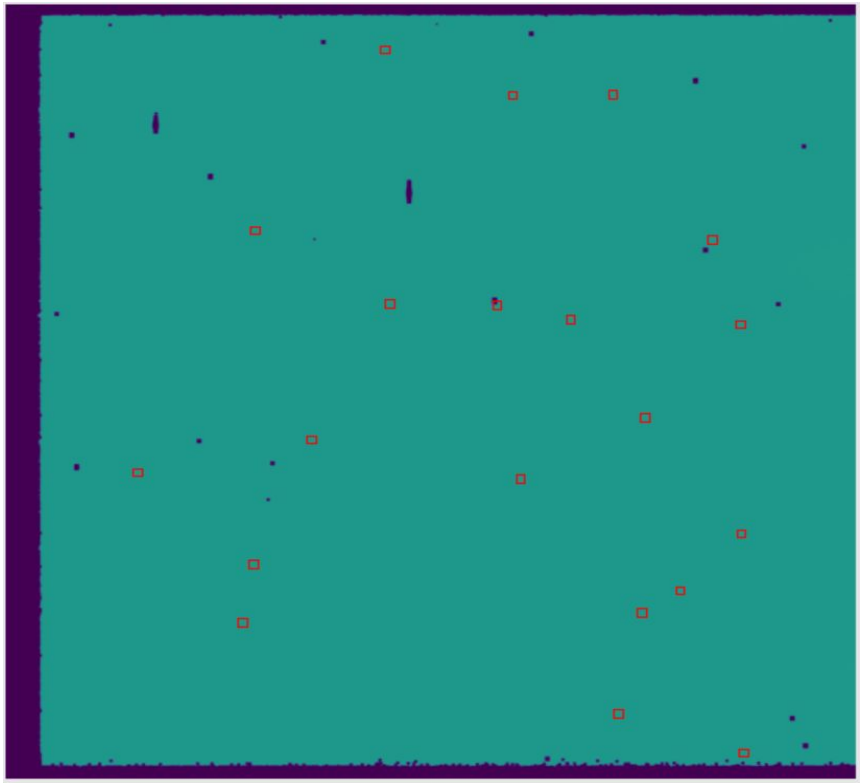
Main Challenge - Intro

Asteroid Detection

	magnitude	length	angle	box
0	16.104747	1	228.358088	galsim.BoundsI(2139,2240,1925,2026)
1	18.222819	3	165.819034	galsim.BoundsI(2131,2234,476,579)
2	15.979216	1	281.243538	galsim.BoundsI(812,913,1147,1248)
3	18.184195	2	95.195193	galsim.BoundsI(2352,2454,1006,1108)
4	16.298675	3	356.967492	galsim.BoundsI(2080,2183,466,569)
5	16.305862	2	56.170222	galsim.BoundsI(1654,1756,2119,2221)
6	16.967739	1	211.522894	galsim.BoundsI(1543,1644,1406,1507)
7	18.127119	1	270.145747	galsim.BoundsI(2707,2808,1119,1220)
8	15.172116	2	153.090408	galsim.BoundsI(2140,2242,2428,2530)
9	17.504909	3	295.527269	galsim.BoundsI(1139,1242,2915,3018)
10	15.029287	3	332.281818	galsim.BoundsI(871,974,110,213)
11	17.396485	3	96.447372	galsim.BoundsI(224,327,1743,1846)
12	18.680659	1	79.306272	galsim.BoundsI(1078,1179,2589,2690)
13	17.984784	3	272.557400	galsim.BoundsI(1659,1762,103,206)
14	15.566666	1	305.983155	galsim.BoundsI(1300,1401,2083,2184)
15	18.794665	2	180.476585	galsim.BoundsI(523,625,1734,1836)
16	15.269838	1	67.397933	galsim.BoundsI(1847,1948,1343,1444)
17	16.462608	3	123.557740	galsim.BoundsI(2617,2720,2903,3006)
18	17.662699	1	128.526359	galsim.BoundsI(2613,2714,500,601)
19	15.841308	3	137.533233	galsim.BoundsI(449,552,2121,2224)]

- Every big (approx. 3000x3000) difference images has a Pandas DataFrame
- Streaks are objects moving in a straight line (asteroids in this case).
- Magnitude = Magnitude of the streak
- Length = Length of the streak
- Angle = Angle of the streak
- Box coordinates of the injected asteroids
  - width = ‘length’ + 100
  - height = ‘length’ + 100

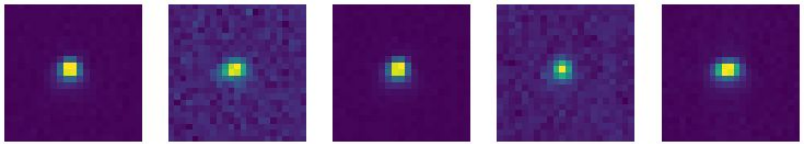
Main Challenge - Intro



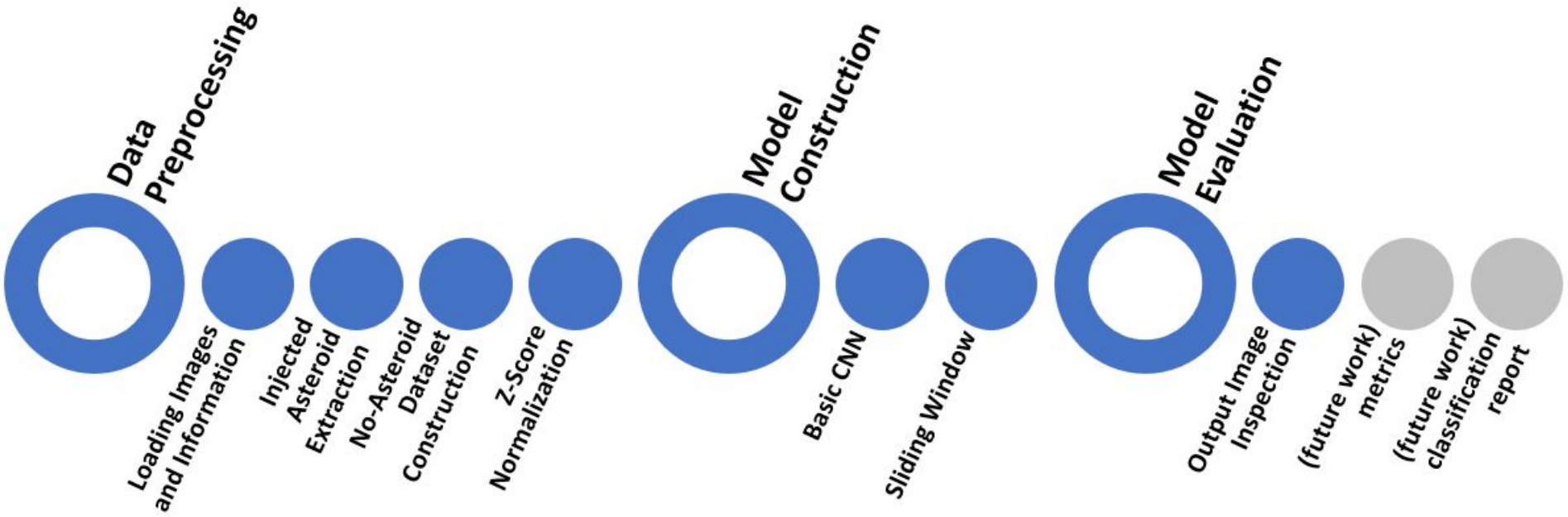
Aim

- Detect the presence of asteroids in the big (3080x3072 px) difference images.
- 26x26 boxes around injected asteroids (given targets)
- Asteroid images (around red boxes) were extracted to get an asteroid class data set.

Individual Asteroid Images (26x26)

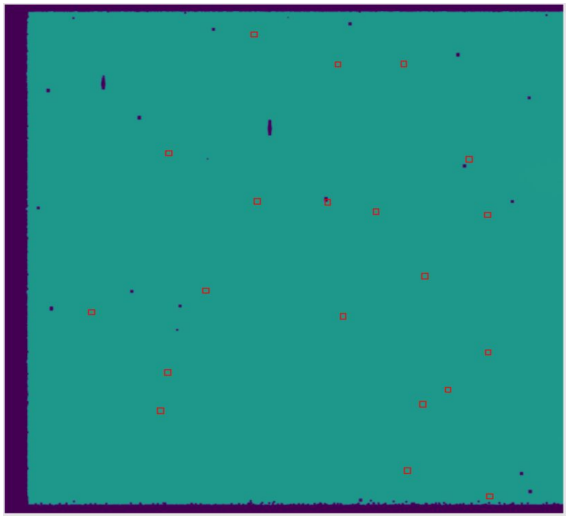


Main Challenge - Methodology



Main Challenge - Methodology

Data Preprocessing



- Red boxes are the injected asteroids

No-Asteroid Data Set

- Difference images was randomly sampled with a 50/50 split between asteroid and no-asteroid sample numbers.
- Samples were checked to ensure they were not within injected asteroid boxes.
- (26x26)

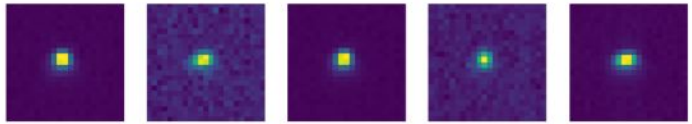
Z-Score Normalization

- Normalized to improve model metrics.

Asteroid Data Set

- Collected using `asteroid_injected_information_#.npz` files and difference images.
- (26 x 26)

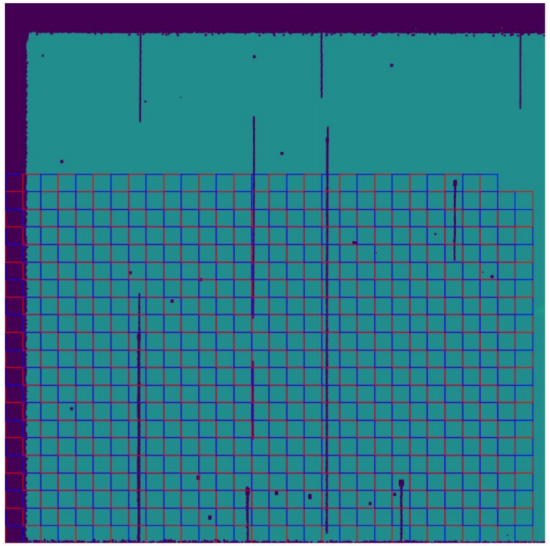
Individual Asteroid Images (26x26)



Main Challenge - Methodology

Model Construction

Sliding Window Model



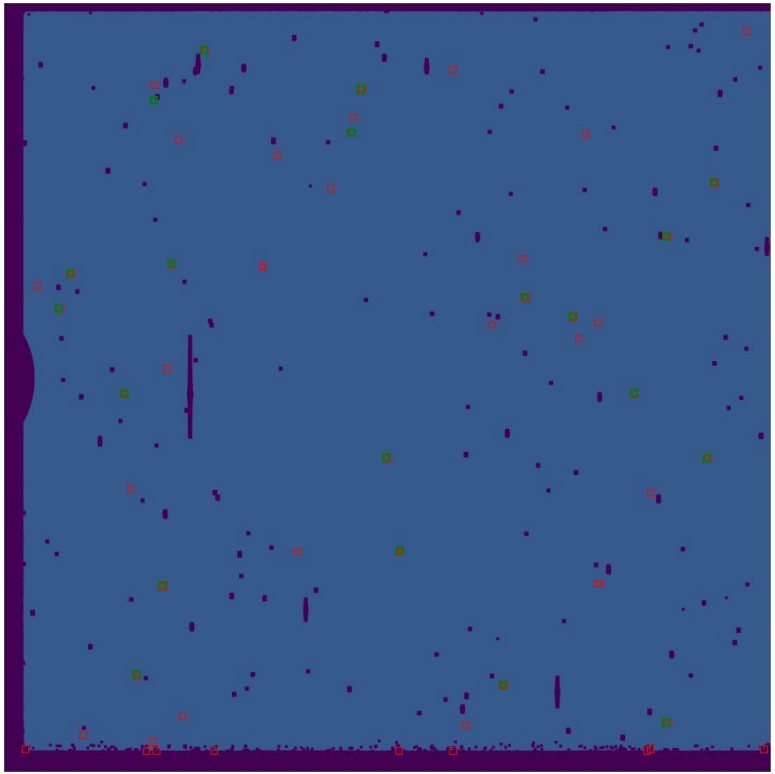
- This was exaggerated (200x200 images)
  - In reality it is (26x26 images)

Basic Convolutional Neural Network

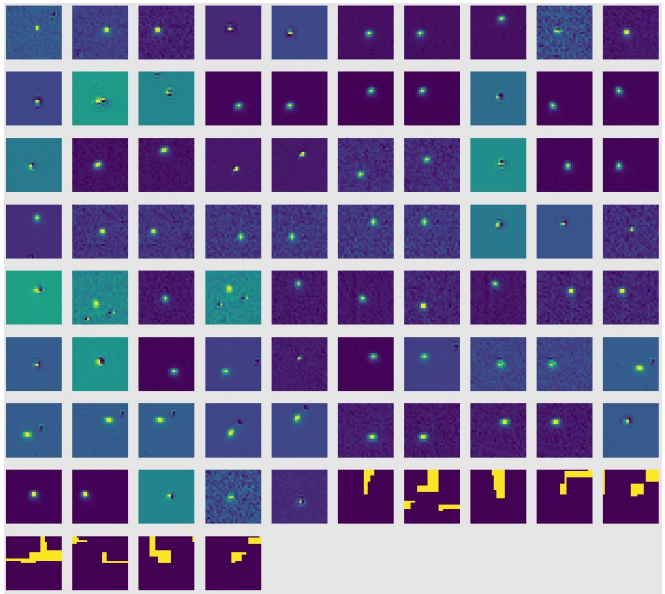
```
import torch.nn.functional as F

class basic_CNN(torch.nn.Module):
    def __init__(self):
        super(basic_CNN, self).__init__()
        self.conv1 = torch.nn.Conv2d(in_channels=n_bands, out_channels=6, kernel_size=
        self.pool = torch.nn.MaxPool2d(kernel_size=4, stride=2)
        self.conv2 = torch.nn.Conv2d(in_channels=6, out_channels=3, kernel_size=4)
        self.fc1 = torch.nn.Linear(in_features=12, out_features=120)
        self.fc2 = torch.nn.Linear(120, 500)
        self.fc3 = torch.nn.Linear(1000, 500)
        self.fc4 = torch.nn.Linear(500, 2)
        self.dropout = torch.nn.Dropout(0.2)

    def forward(self, x):
        x = self.conv1(x)
        x = F.relu(x)
        x = self.pool(x)
        x = self.conv2(x)
        x = F.relu(x)
        x = self.pool(x)
        x = torch.flatten(x, 1)
        x = self.fc1(x)
        x = F.relu(x)
        x = self.dropout(x)
        x = self.fc2(x)
        x = F.relu(x)
        x = self.dropout(x)
        x = self.fc3(x)
        x = F.relu(x)
        x = self.dropout(x)
        x = self.fc4(x)
        return x
```

```
def forward(self, x):
    x = self.conv1(x)
    x = F.relu(x)
    x = self.pool(x)
    x = self.conv2(x)
    x = F.relu(x)
    x = self.pool(x)
    x = torch.flatten(x, 1)
    x = self.fc1(x)
    x = F.relu(x)
    x = self.dropout(x)
    x = self.fc2(x)
    x = F.relu(x)
    x = self.dropout(x)
    x = self.fc3(x)
    x = F.relu(x)
    x = self.dropout(x)
    x = self.fc4(x)
    return x
```

Main Challenge - Results



Matrix of images believed to be asteroids

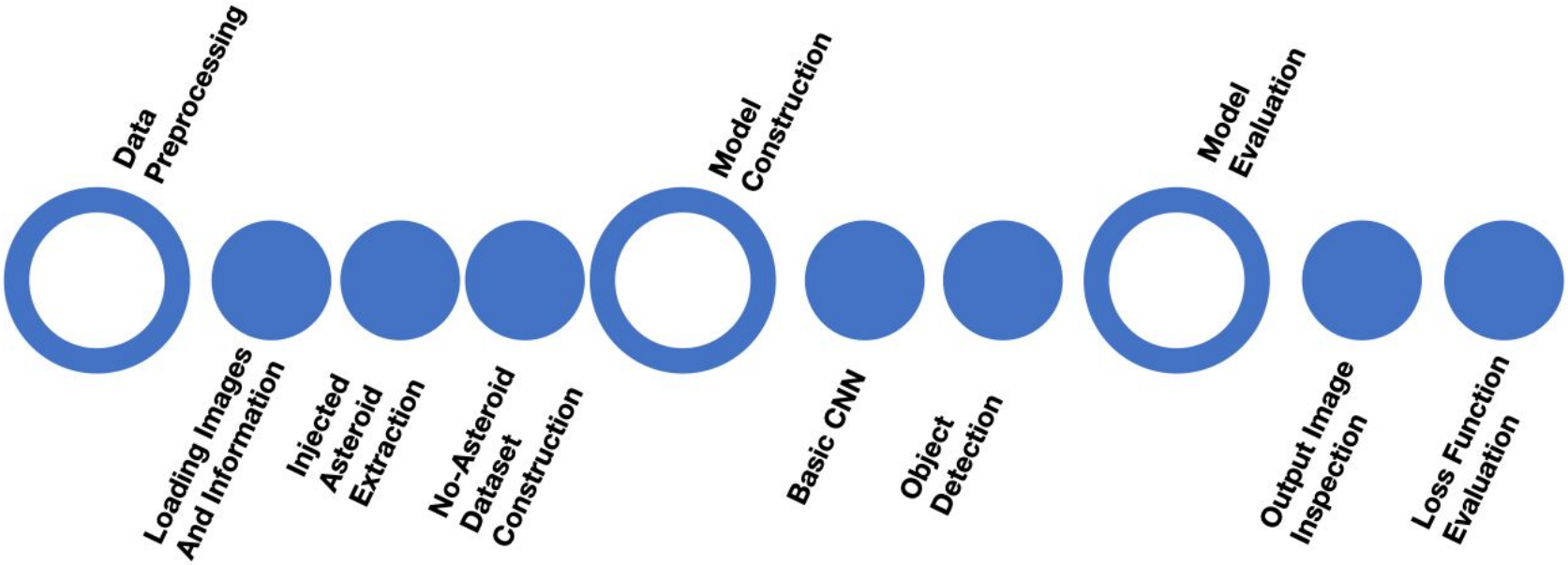


Confidence = 1.0
Threshold > 0.99
Sliding_shift = 7 px

- Sliding window yielded results
- Notice the last predictions were inaccurate
  - Future work needed
- We do not have model metrics yet

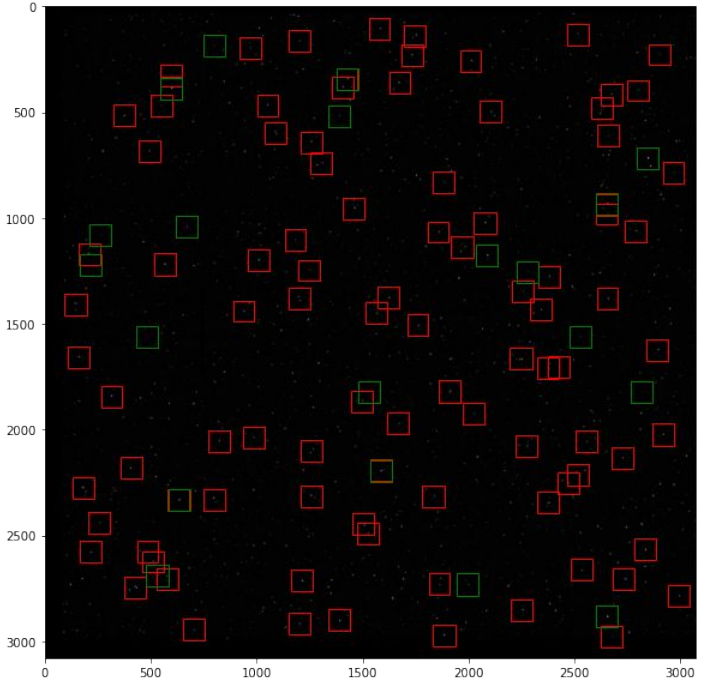
Main Challenge - Methodology

Alternative using Object Detection



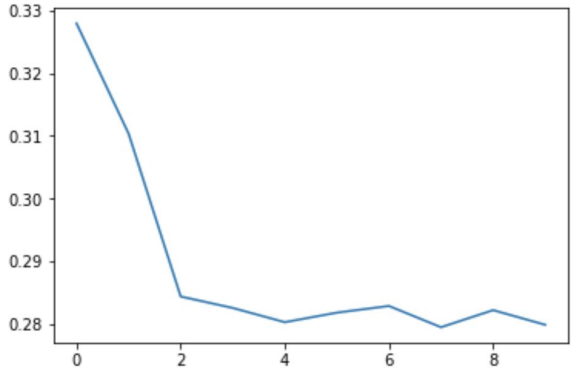
Main Challenge - Methodology

Alternative using Object Detection

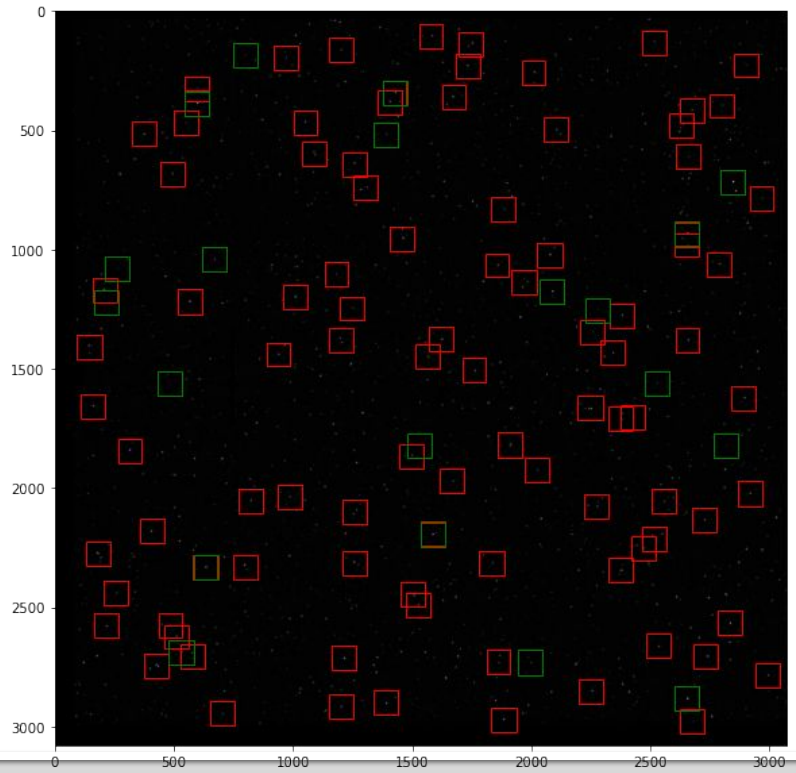


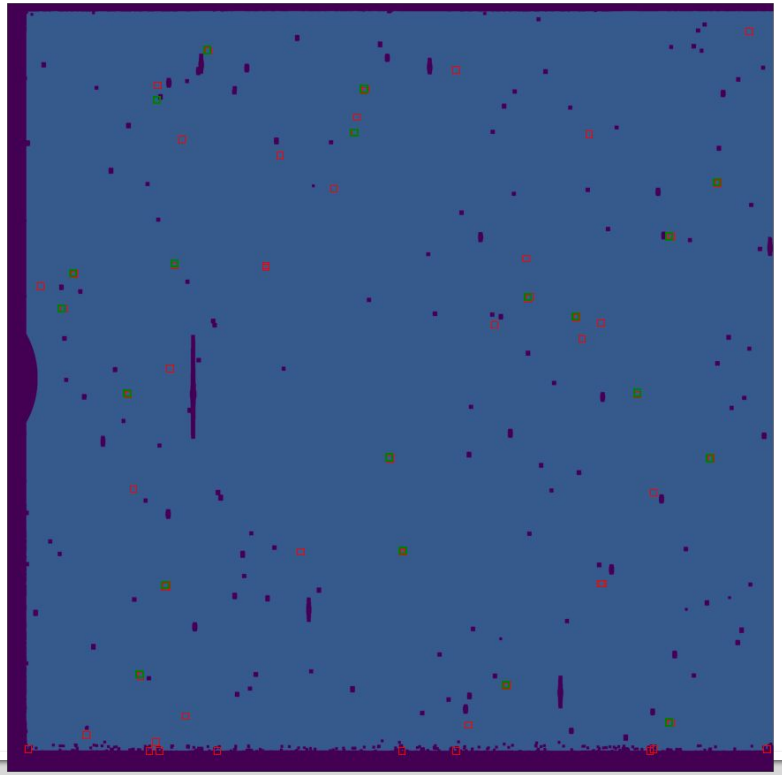
Set up

- 70/30 Train/Val Data Split
- Extract Asteroid locations on the given images
- Train Object detection Algorithm on data



Main Challenge - Methodology





Summary

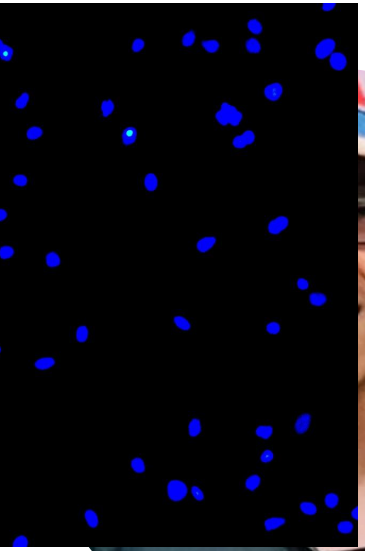
Mini Challenge:

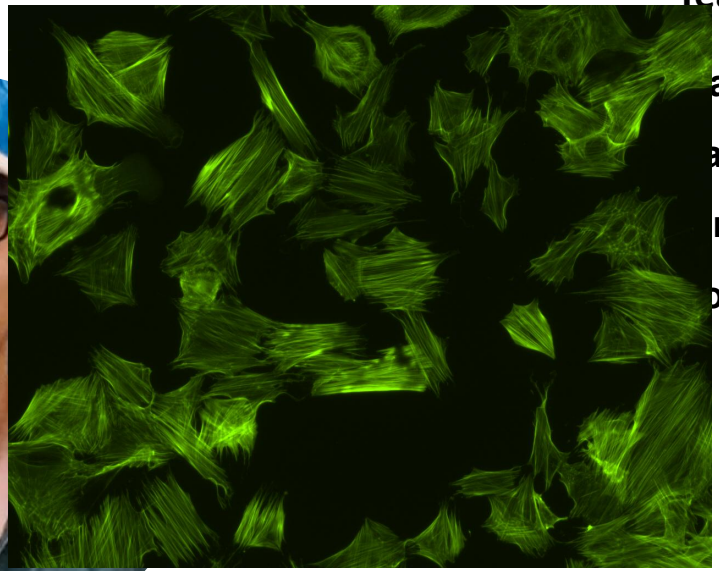
- We implemented 3 models (MLP, CNN, ResNET) to perform classification.
- All the three models yielded similar results.
- Trained CNN model on subset of bands and found the metrics to be fairly similar.

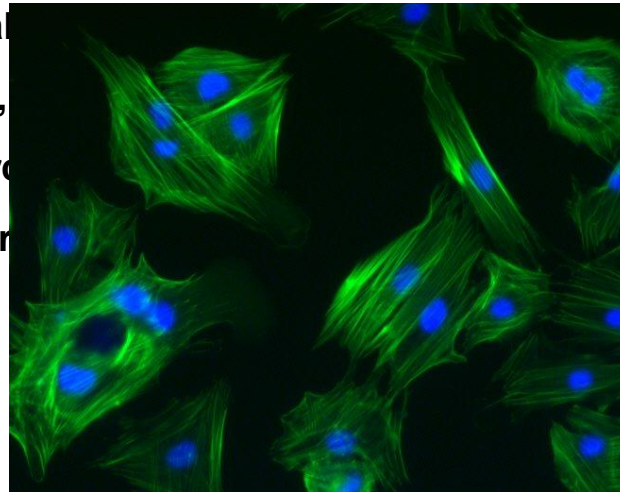
Major Challenge:

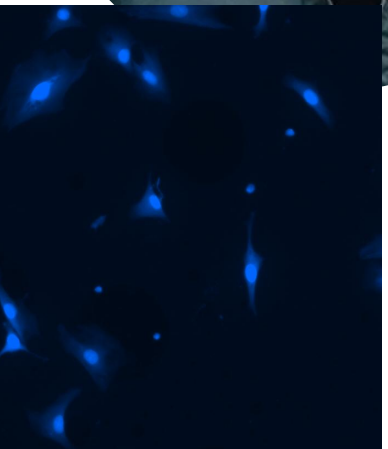
- Devised two ways of locating asteroids with two CNN models
  - Sliding Window Method
  - Region Proposal Network
- Compared visual results side by side
- With more time, will be able to predict true asteroids among the matrix of observed asteroids

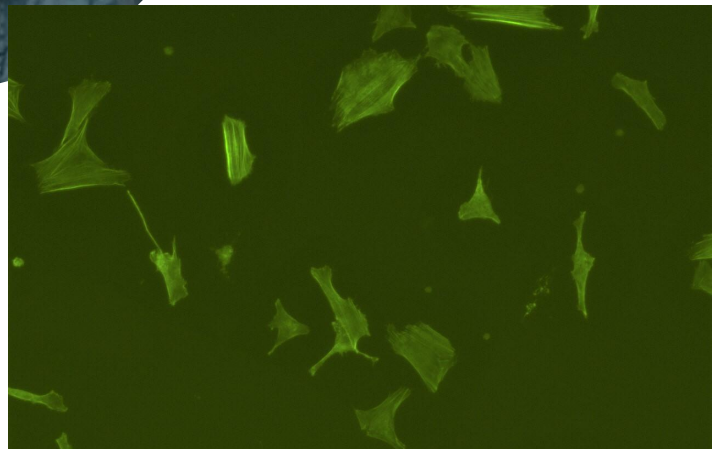
Team 4: Dongwei Sun

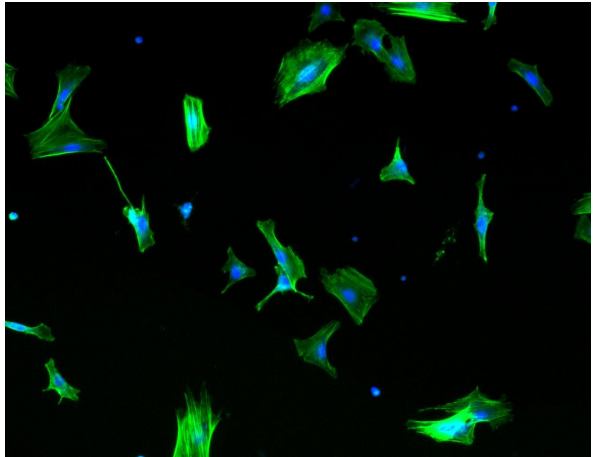












Team 4: Ivan Neto

Degree: Computer Science Undergraduate

Skills: Python, Keras, Scikit-learn

Things learned: PyTorch, Anaconda, Basic Astronomy, Working with Images

With more time: PyTorch in depth, optimizing my models better, regularization in depth

Team 4: Ponmanikandan Velmurugan (Mani)

Degree: Masters' in Computer Science

Skills: Python, Numpy, Pandas, Sklearn

Things learned: Pytorch, Neural Networks, GitHub, Big datasets, Image processing

With more time: K-fold cross validation, Different models, Modelling with GPU

Team 4: Kaichun Chen(Kevin)

Degree:Physics Undergraduate

Skills:Python

Things learned:PyTorch, Working with Images

With more time:Get familiar with Pytorch, using and optimizing models.

Team 4: Julin

Degree: Masters of Science in Computer Science

Skills: Python, Detecto, Pytorch

Things learned: Detecto, cleaning data

With more time: Get the model more accurate

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