Image Enhancement and Object Recognition For Night Vision Surveillance

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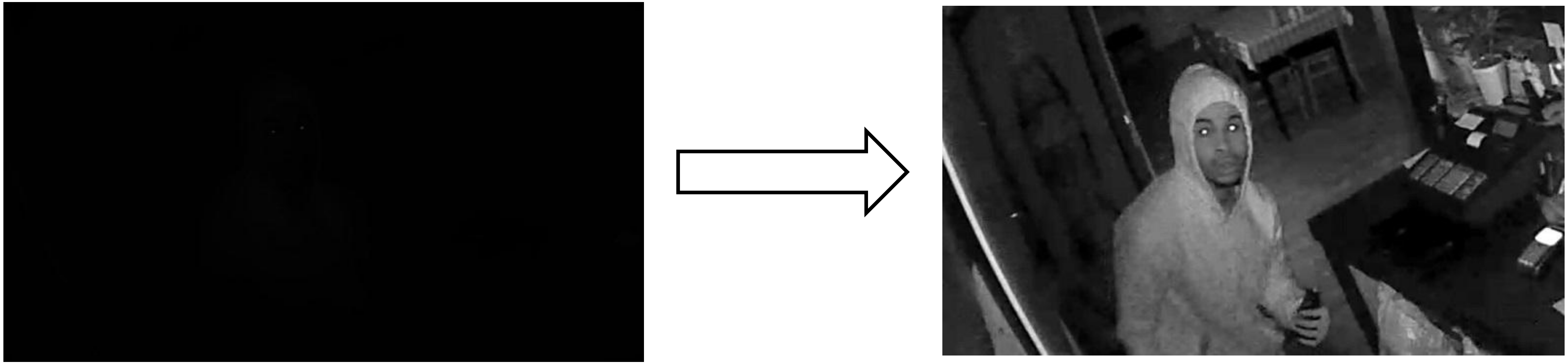
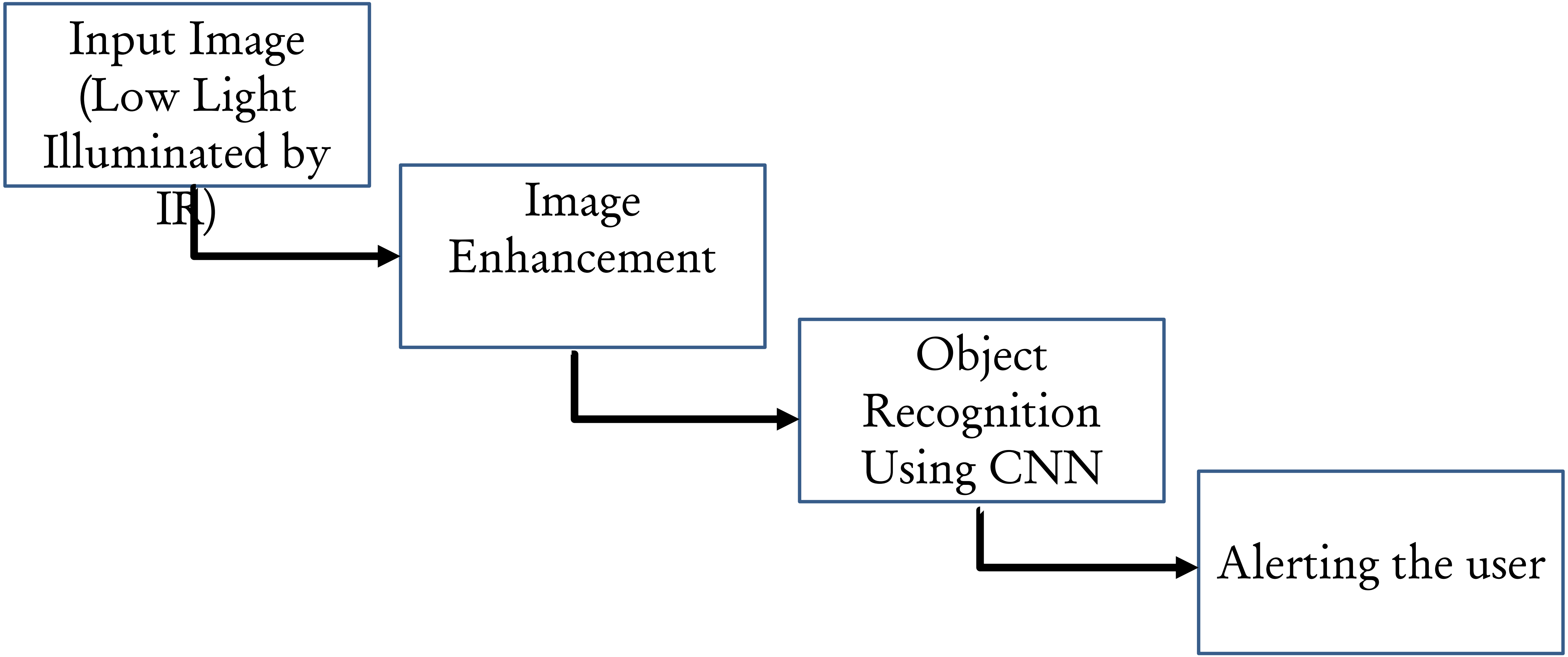
Introduction

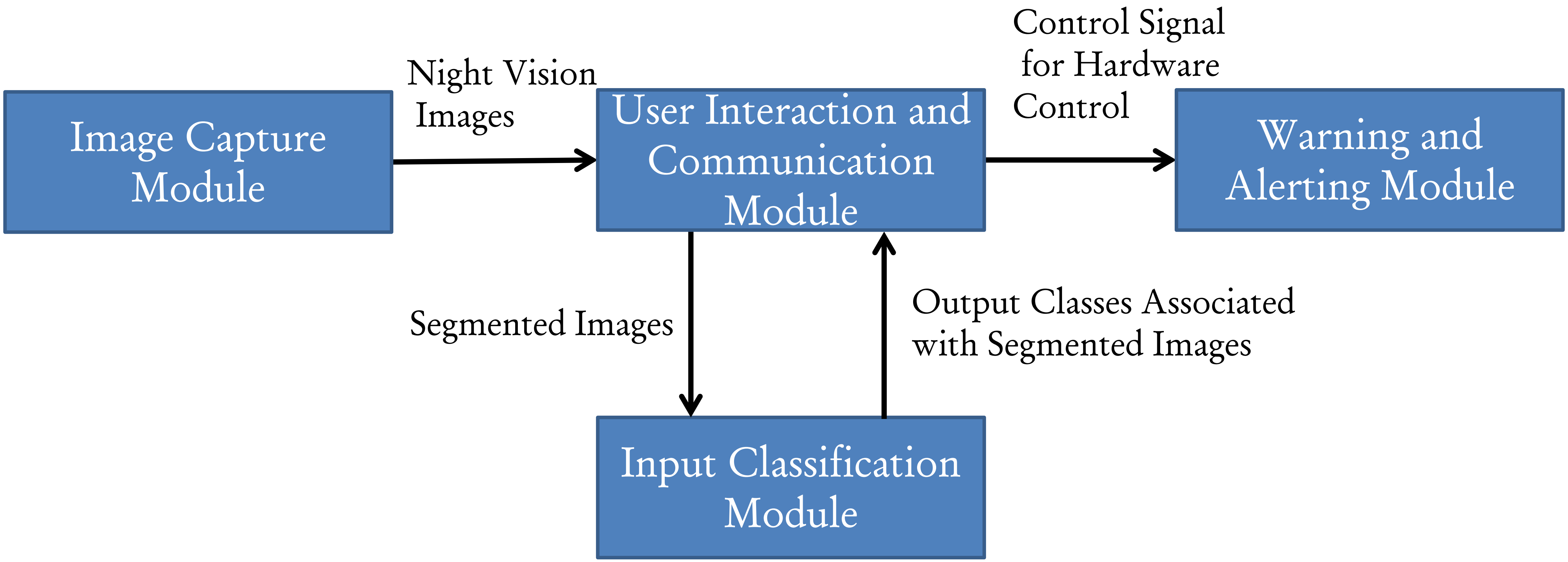
- Image processing and enhancement has been a boon for technological development.
- A machine has been able to see as human does and take necessary actions.
- Sometimes, a machine might see things that a human simply cannot.



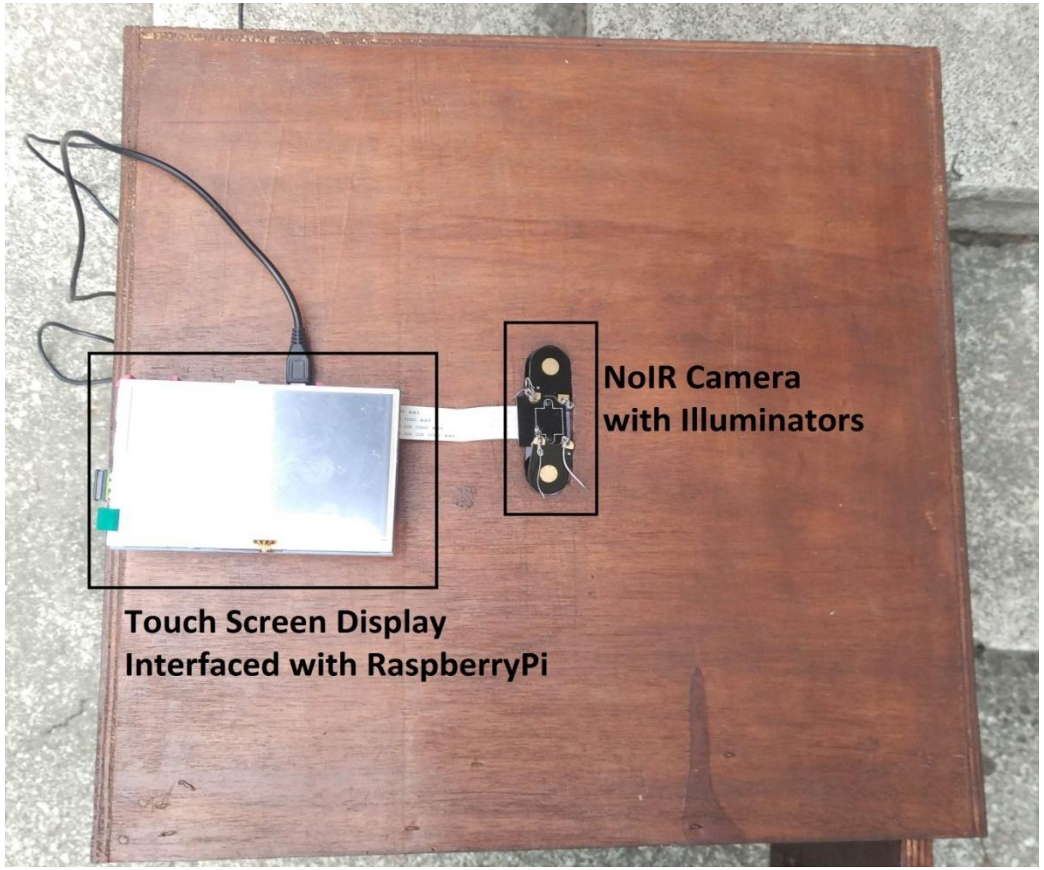
Basic Overview



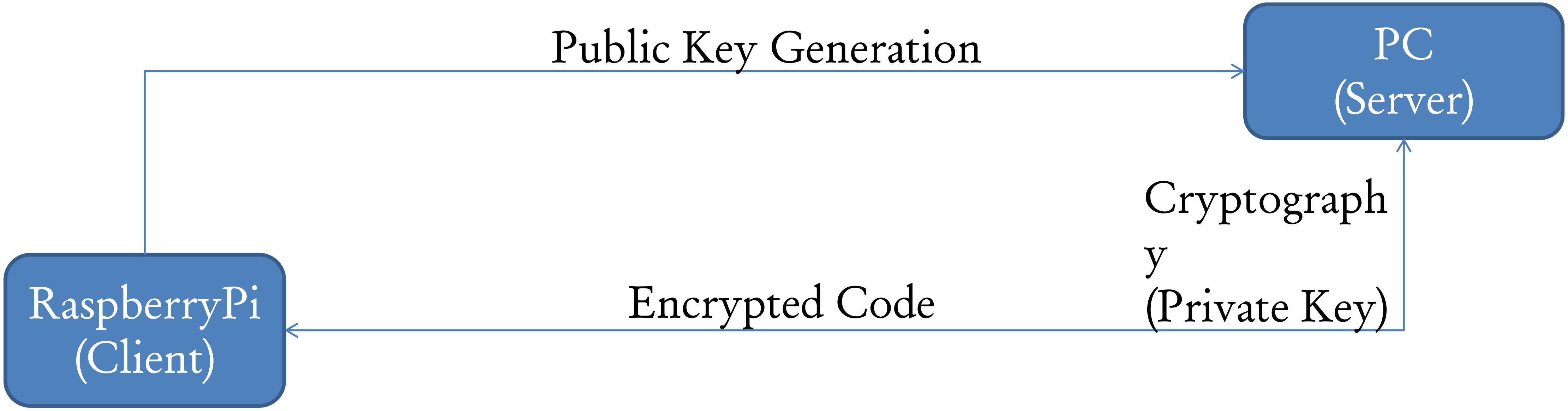
System Block Diagram



Hardware Setup



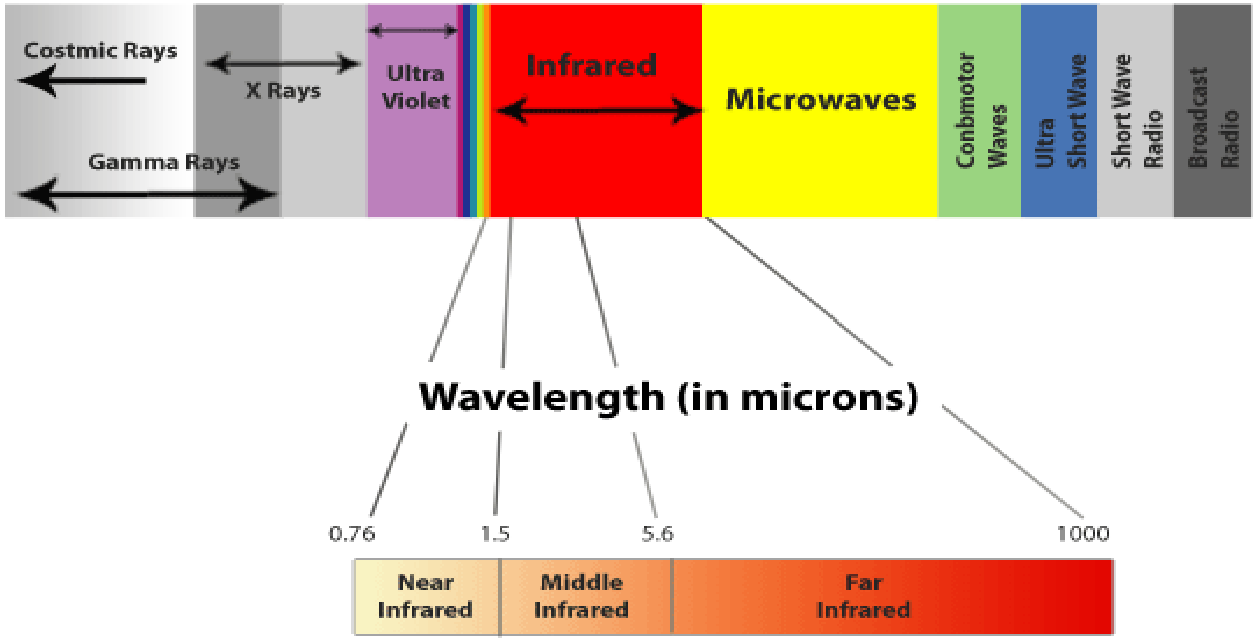
Client-Server Model



- Secure Copy Protocol(SCP)   is used.
- Based on Secure Shell(SSH)
- Key Encryption and decryption makes it less susceptible to network intrusion.

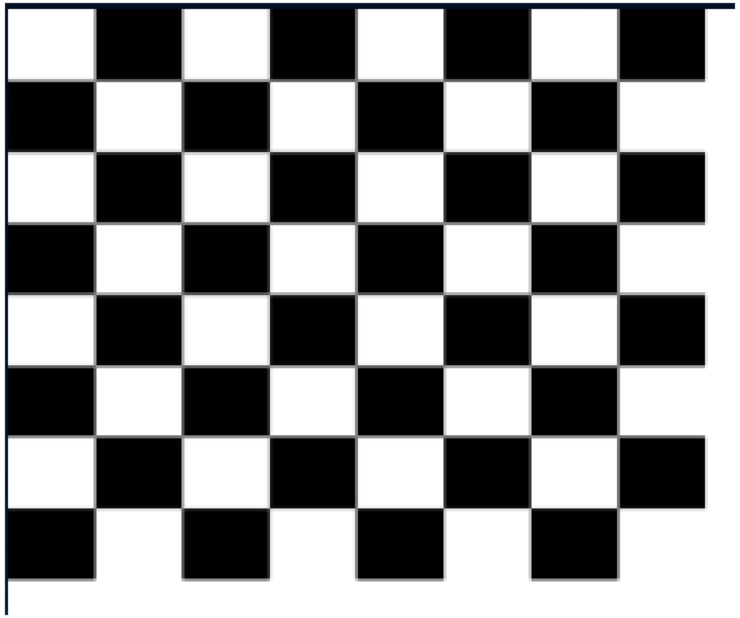
NoIR Camera

- Doesn't have IR Cut Filter.
- Presence of IR illuminators.
- IR rays are invisible to naked human eye.
- Works same as a flash light of mobile phones.

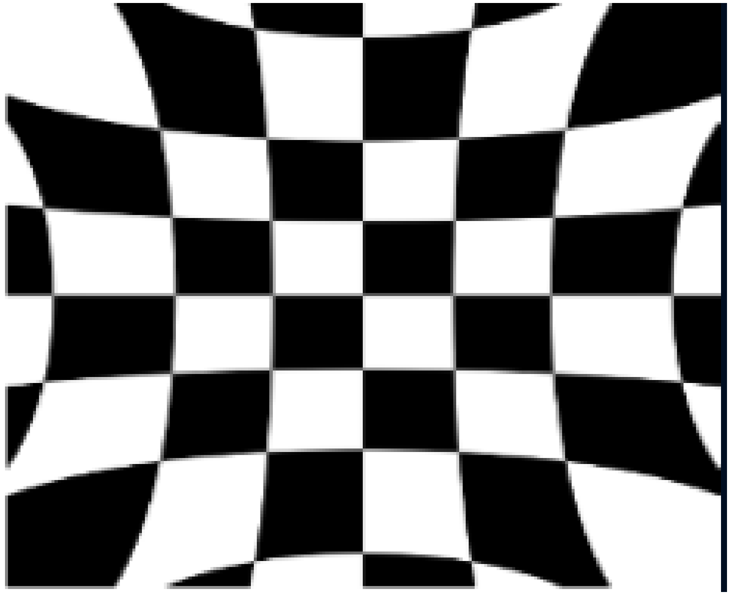


Issues with camera

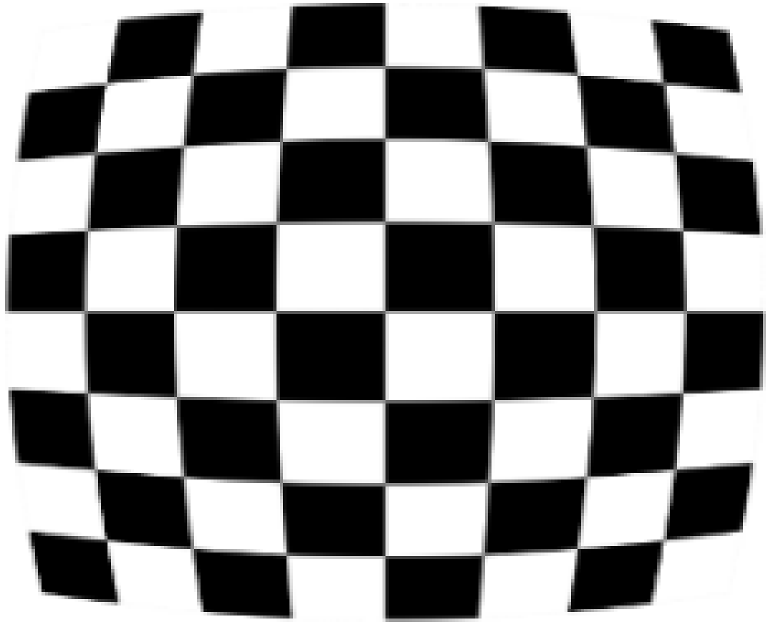
- Radial and Tangential Distortion



No Radial Distortion

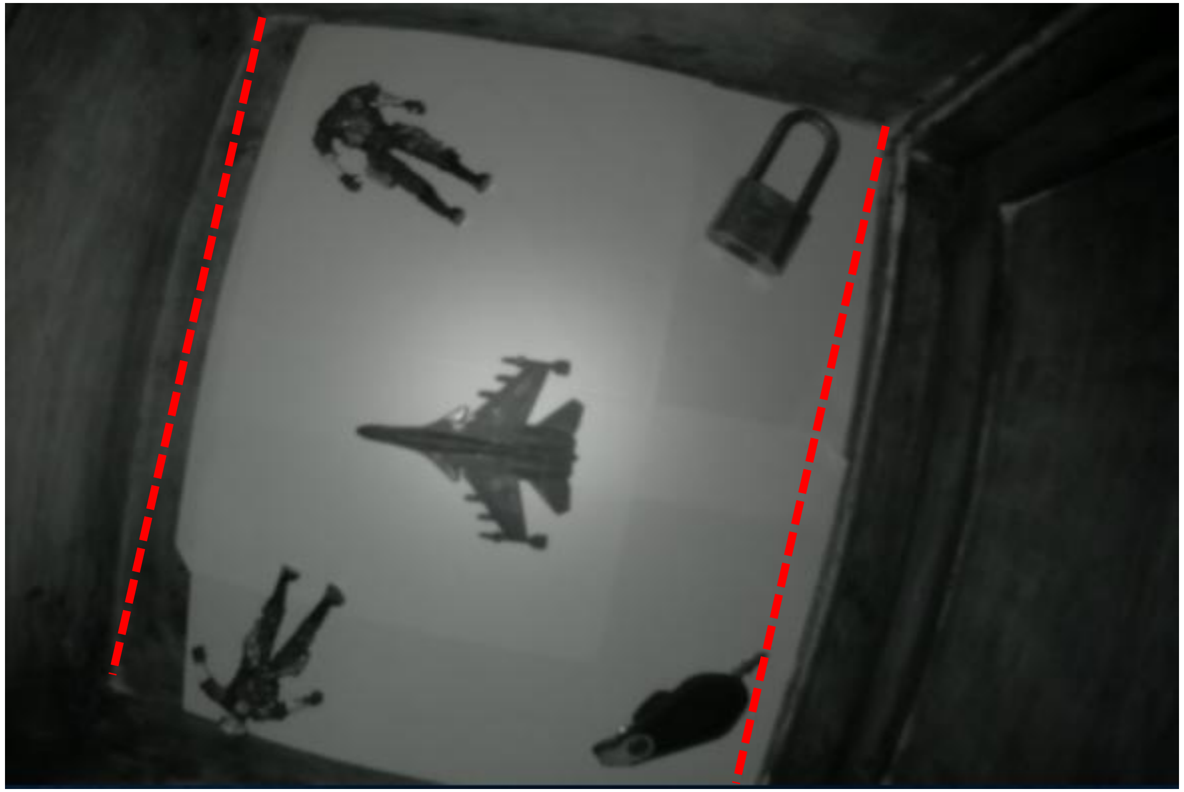


Negative Radial Distortion



Positive Radial Distortion

Solution: Camera Calibration



Distorted Image without Calibration

Undistorted Image After Calibration

Correction using Novel Iterative Method

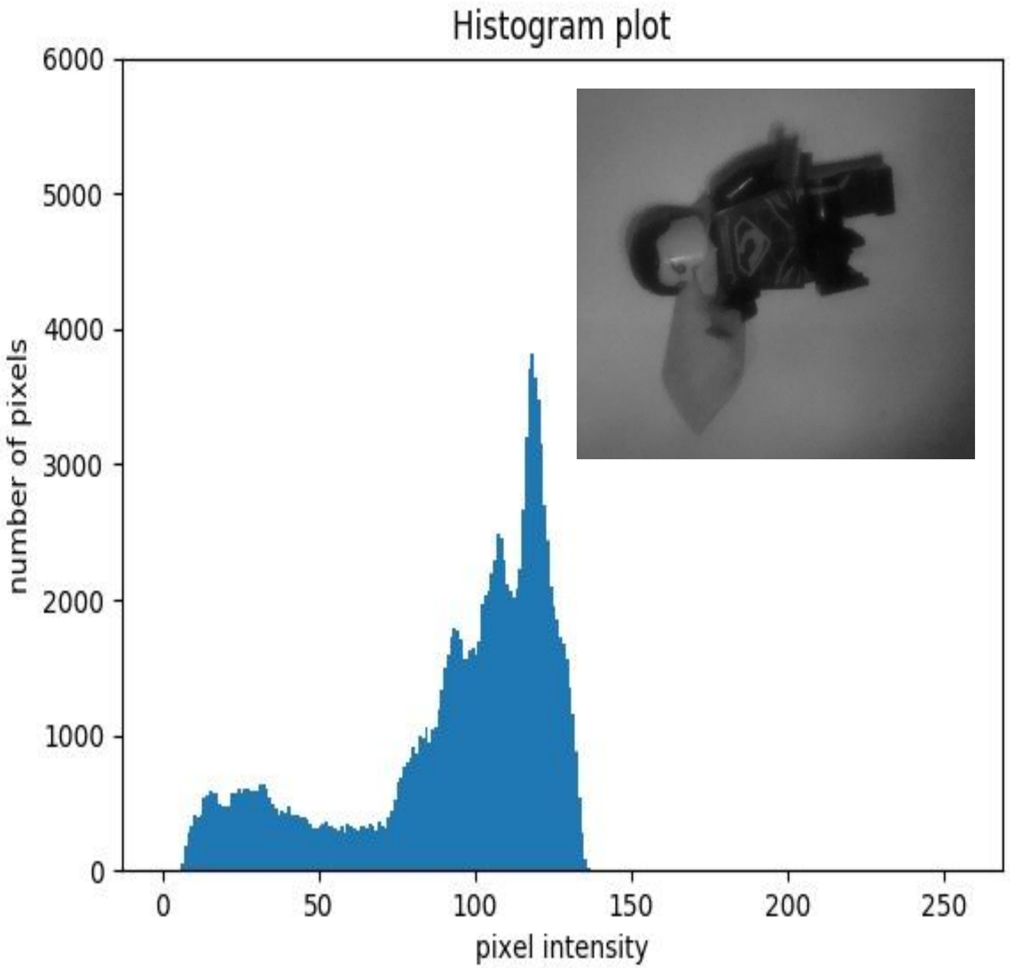
Image Enhancement

- For passive illumination IR cameras, image enhancement is used for Contrast stretching, noise reduction and to provide better input for classifier.

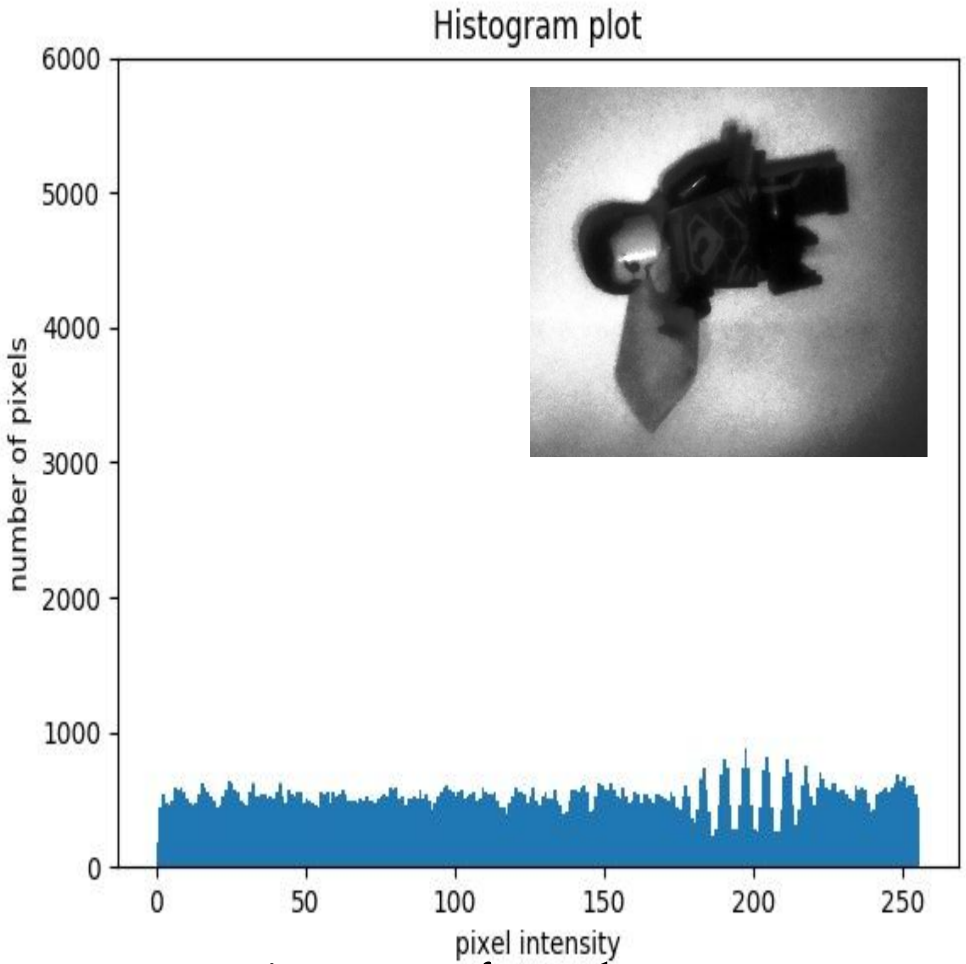
- **Algorithms:**
  - Histogram Equalization,
  - Adaptive Histogram Equalization,
  - Contrast Limited Adaptive Histogram Equalization,
  - Retinex (Single and Multi-scale)

- Quantitative Parameters: Entropy, MSE, PSNR and modified PSNR with variance

Histogram Equalization

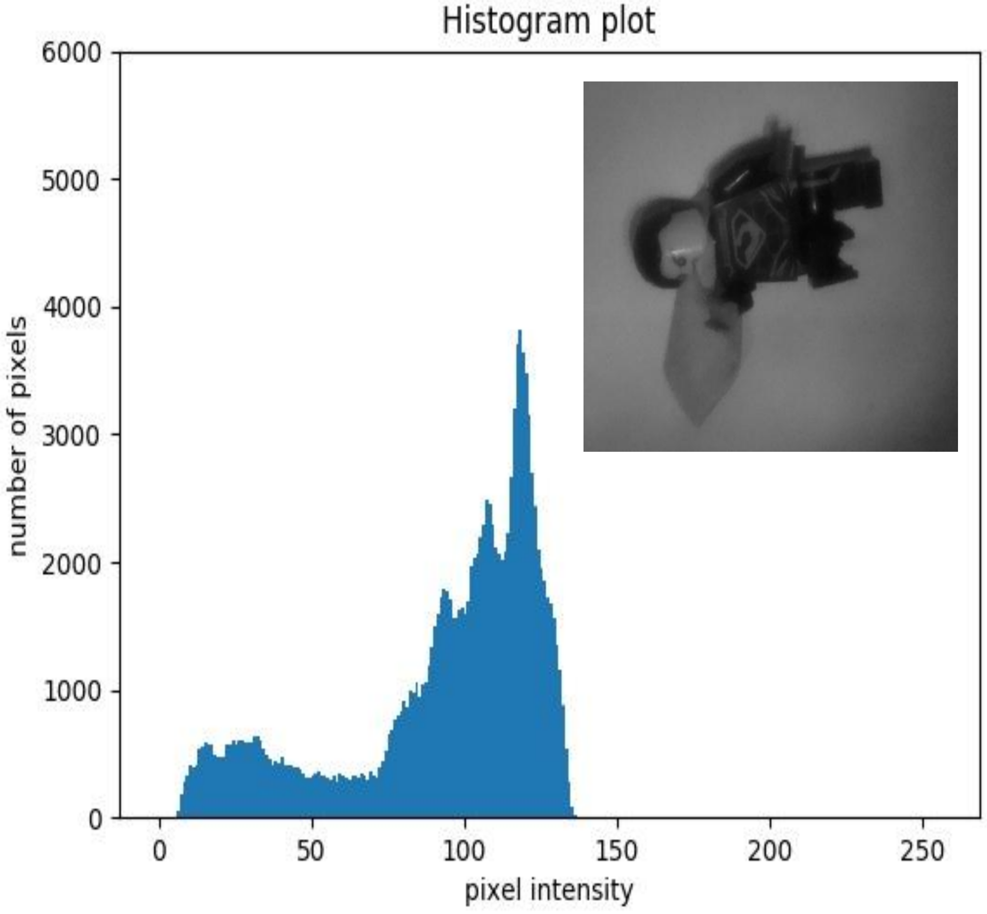


Histogram of Original Image

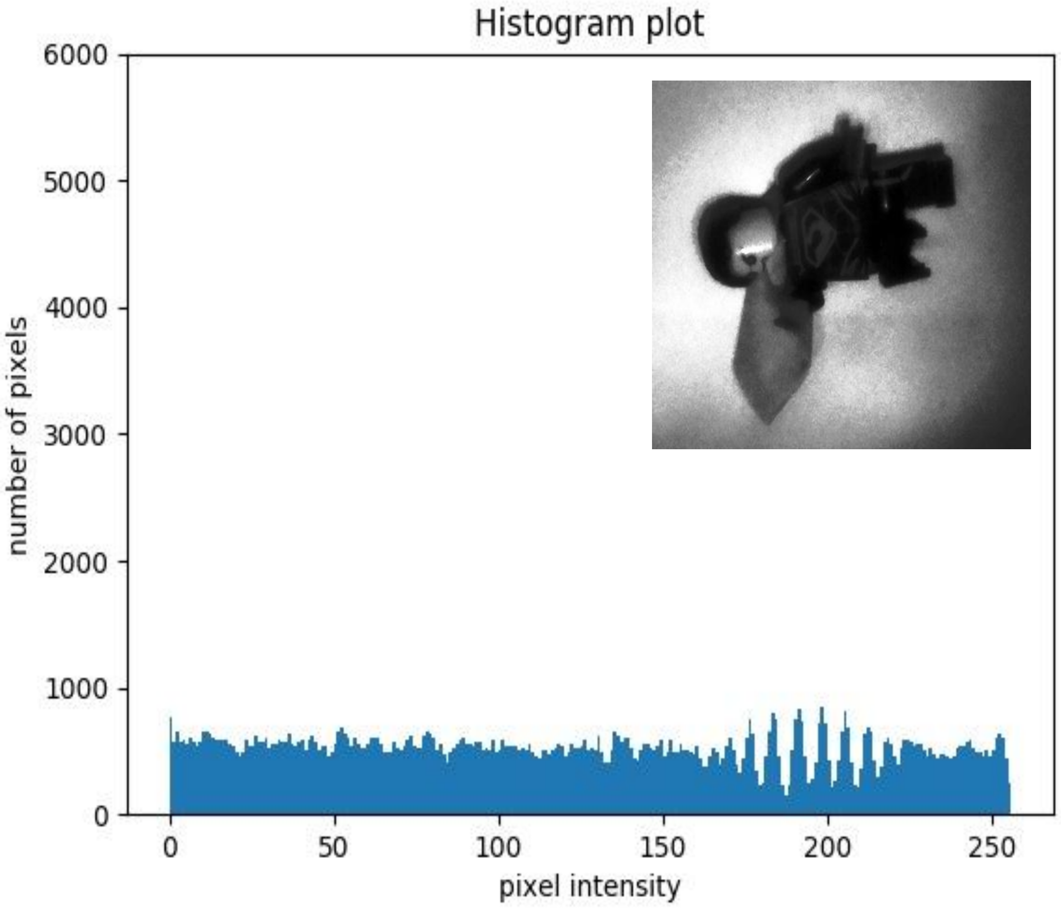


Histogram of Result

Adaptive Histogram Equalization

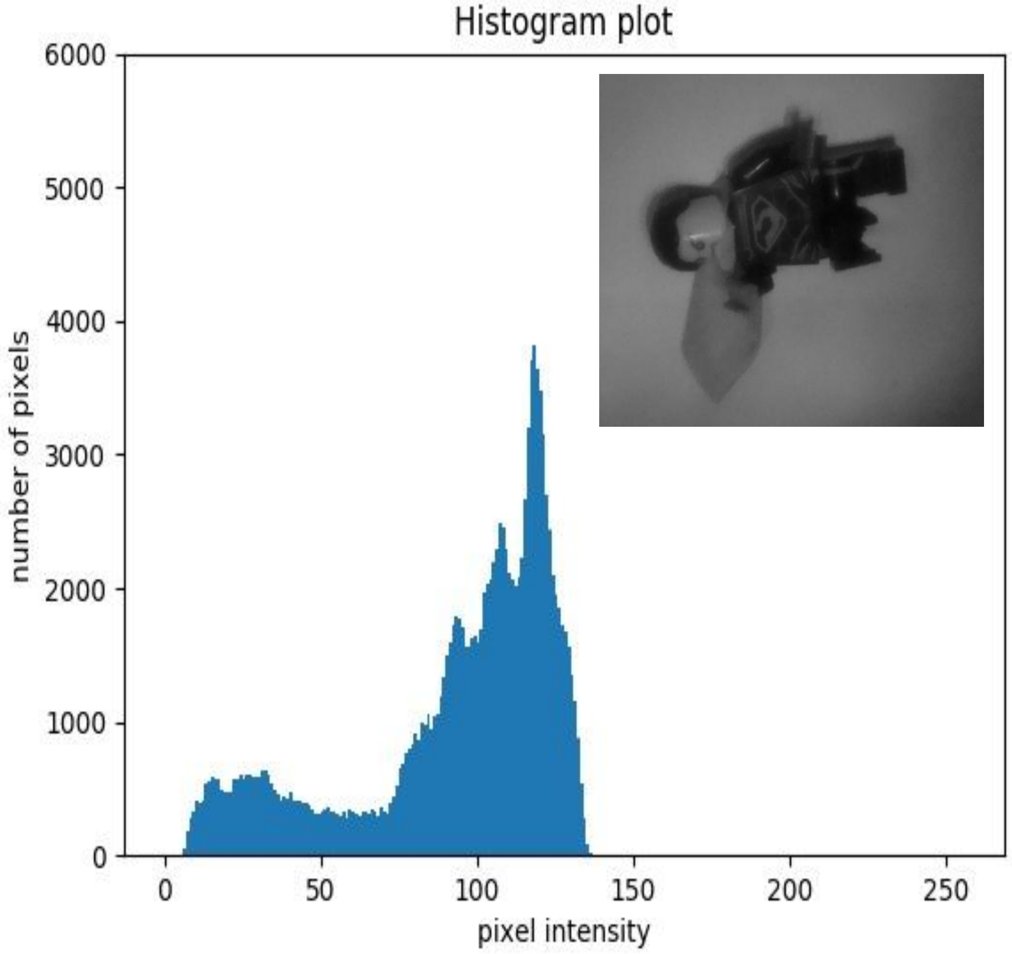


Histogram of Original Image

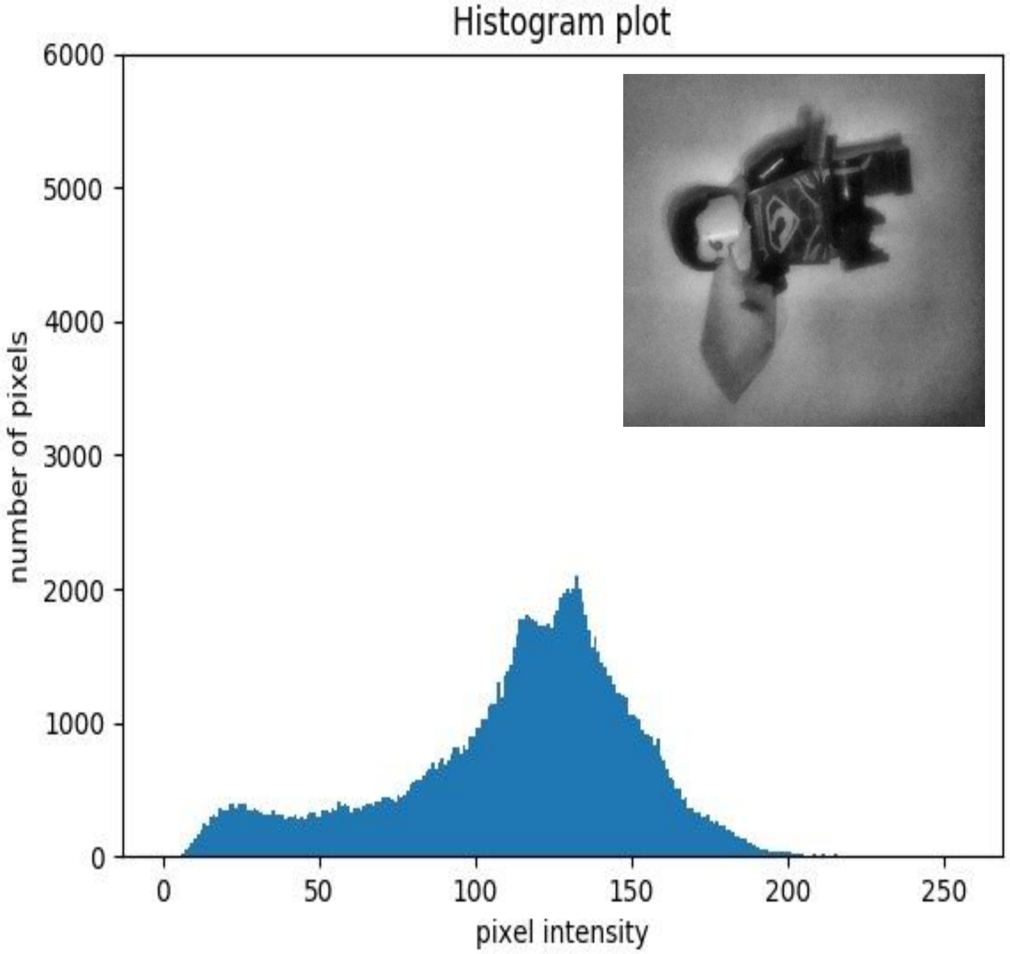


Histogram of Result

Contrast Limited Adaptive Histogram Equalization

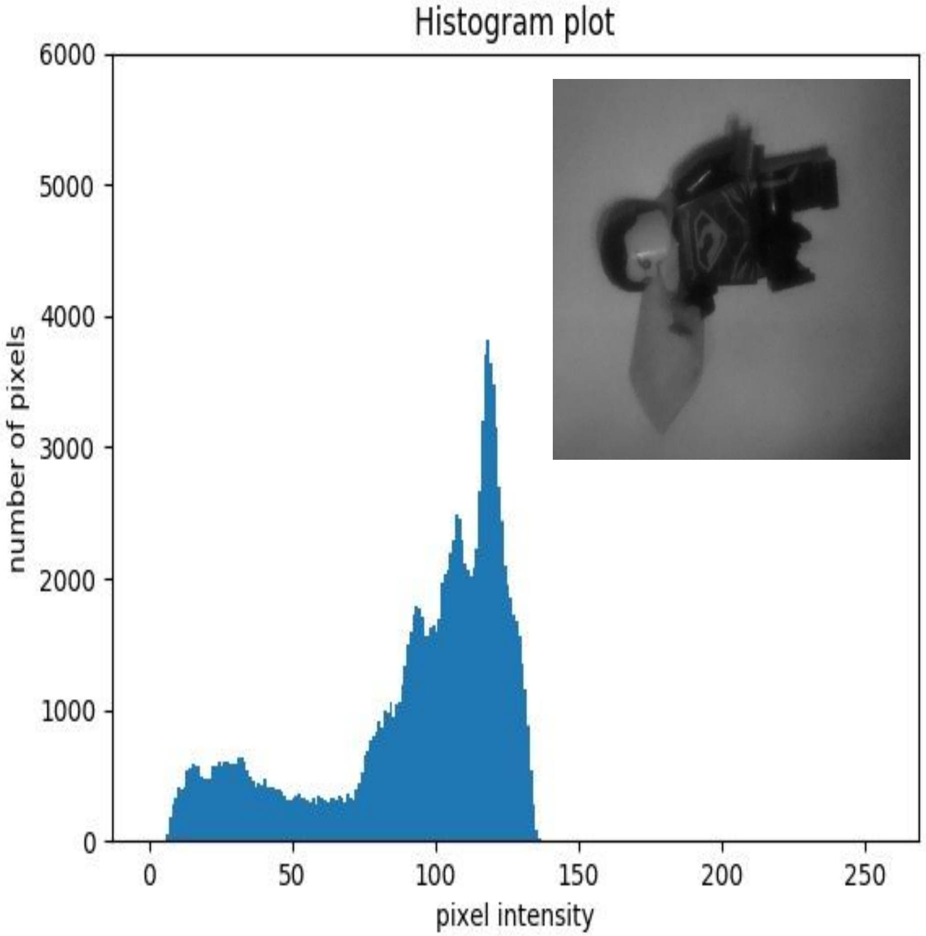


Histogram of Original Image



Histogram of Result

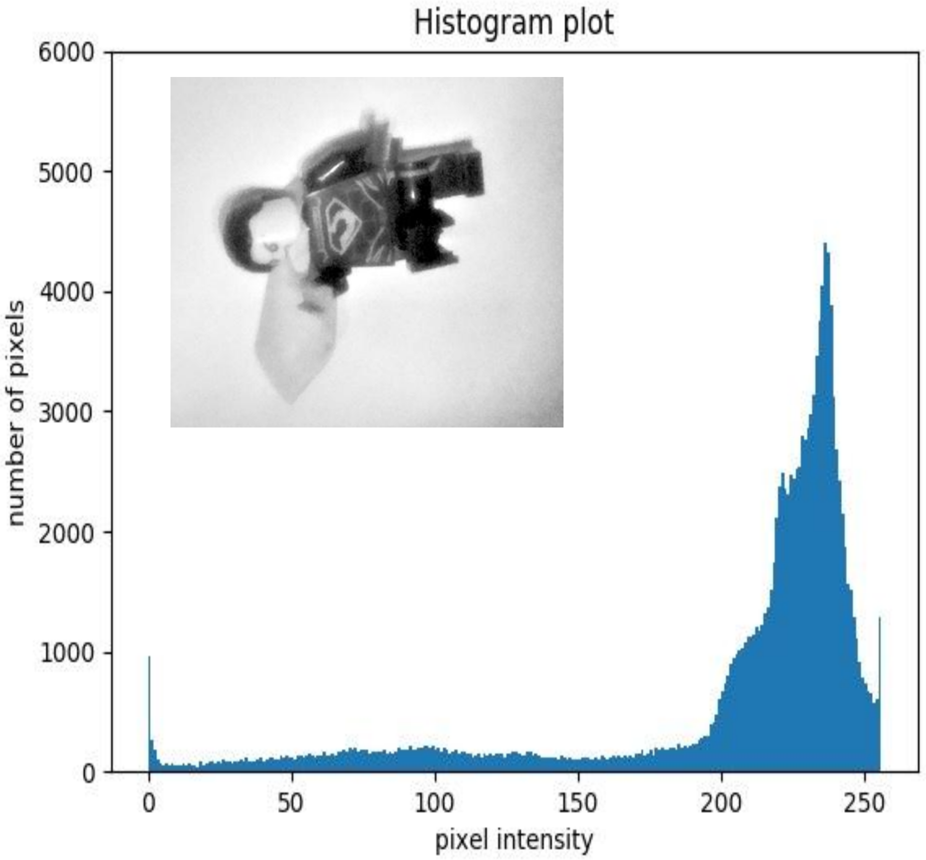
Retinex (Single and Multi-Scale)



MSR Gray

MSR Color

Brightness increase, dynamic range compression



Original image histogram

Same Result of MSR Gray and MSR color (single channe

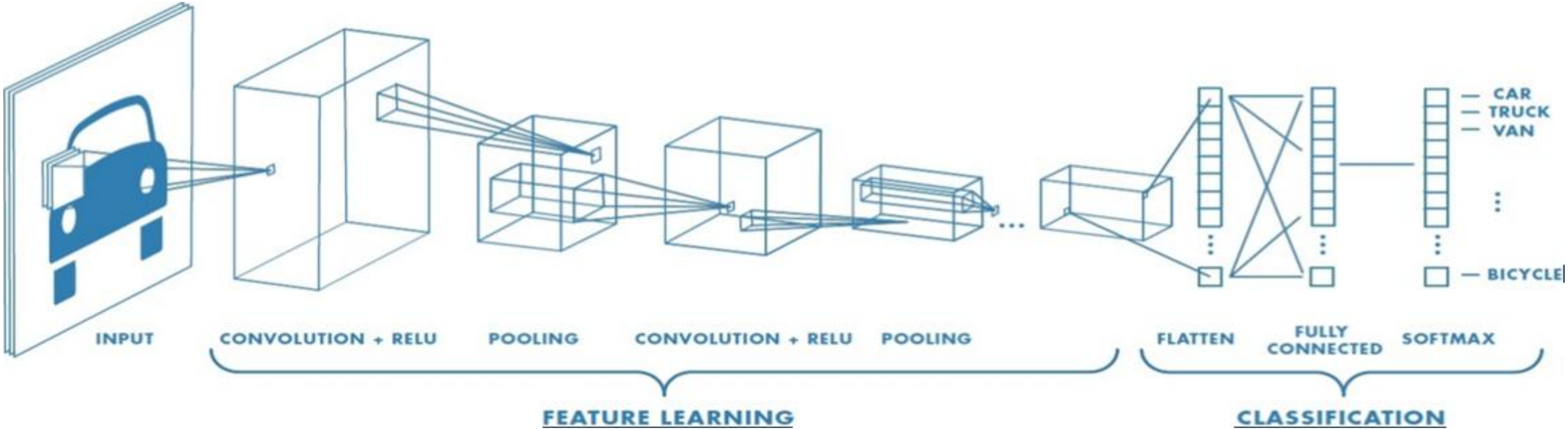
Classification

- Classification methods:
  - Neural Networks,
  - Support Vector Machine (SVM),
  - K – nearest neighbor etc.

- A special type of Neural Network designed specially for image processing called Convolutional Neural Network (CNN) was used.

Convolutional Neural Network (CNN)

- CNNs are best suited for image classification.
- Combination of “Feature Extractor” and “Classifier”.



Convolution Neural Network

Need for CNN

- Convenience: Once model ready, less work to be done.
- Reliability: Provides Spatial Invariance.
- Speed: Classification in fraction of seconds. Takes time only during training.
- Automation: Self-sufficient method with complete automation

Development of Model

- Two approaches for CNN development
  - Development and training of a complete CNN architecture from ground-up.
  - Using "Transfer Learning" approach

Complete CNN training.	Transfer Learning
Refers to complete training of CNN.	Refers to partial training of CNN.
Large dataset needed.	Can work well with smaller datasets.
Needs greater computational power.	Needs less computational power.
Can be more accurate.	Might not be as accurate as complete training.

Comparison table

Transfer Learning

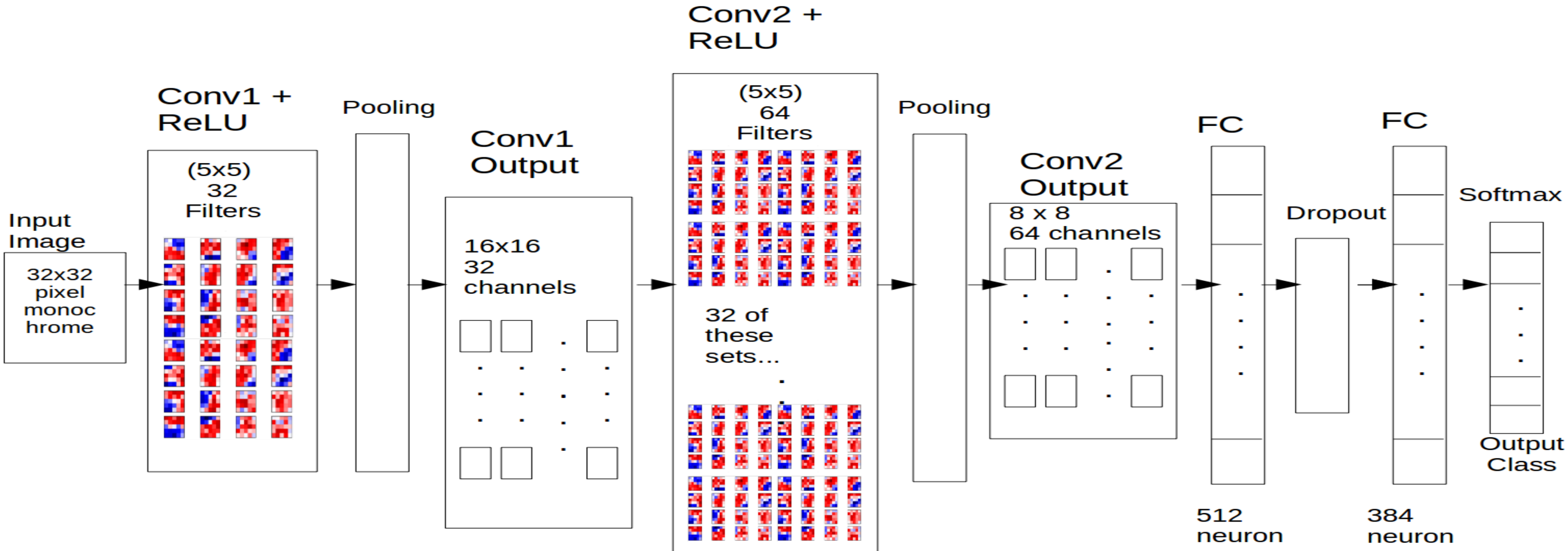
- Training CNN from ground-up is arduous.
- Using a pre-trained network for initialization of weights and biases or used as a fixed feature extractor.
- Weights and biases for Inception V3 model provided by TensorFlow.
- Used the inception model as feature extractor and then trained self made Neural Network.

Transfer Learning

Confusion Matrix obtained from training in our case:

		Predicted Class			
		Batman	Police Man	Soldier	Wonder Woman
Actual Class	Batman	4	4	3	2
	Policeman	0	1	0	3
	Soldier	1	1	4	0
	Wonder Woman	0	2	1	6

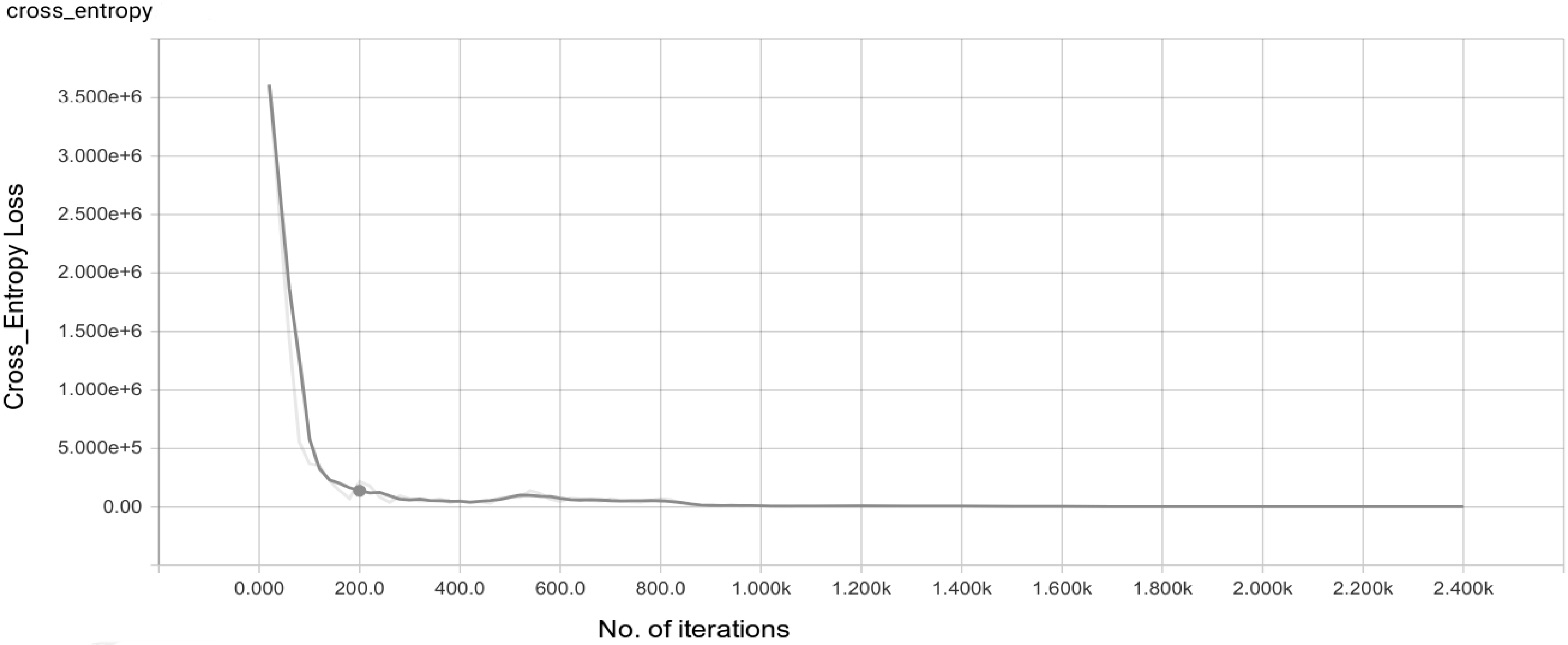
Creating a complete CNN



Our Custom CNN architecture

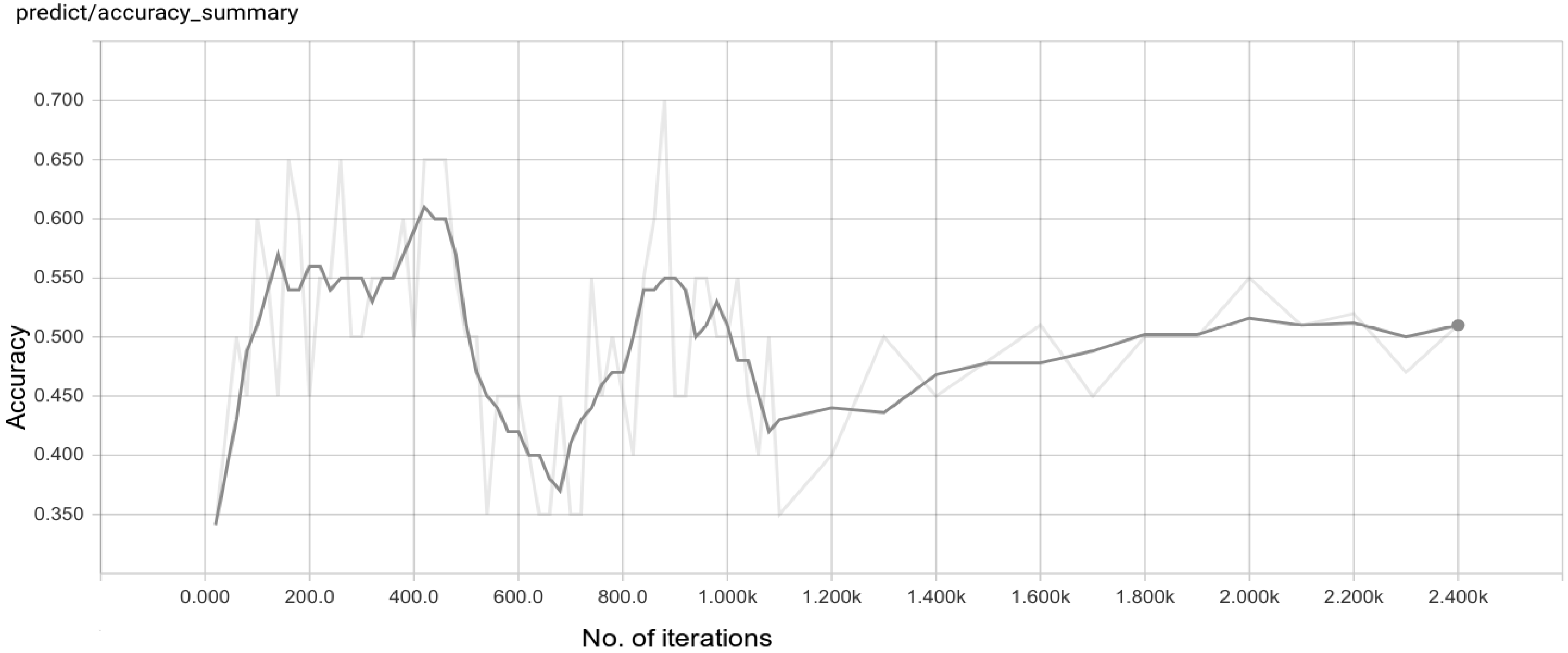
Results of training CNN

COST FUNCTION GRAPH



Results of training CNN

VALIDATION ACCURACY

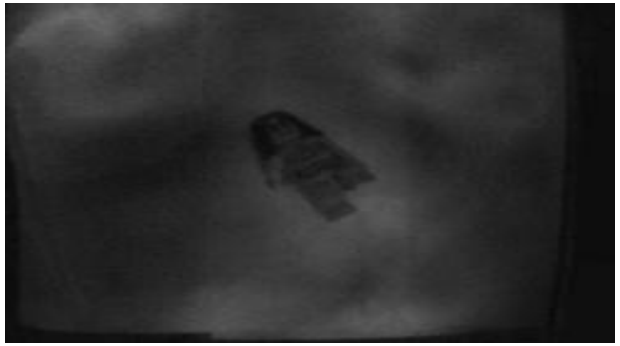


CNN Training Details

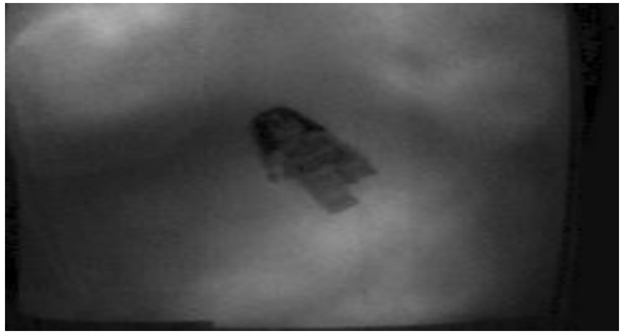
Epoch	Time to complete	Accuracy	Cross Entropy loss
1st	0:29:11	55.71%	200088.573
2nd	1:25:29	46.19%	62718.081
3rd	0:29:17	48.49%	3899.8477
4th	0:26:55	51.25%	2880.0667

Image Processing Effects

Original Image



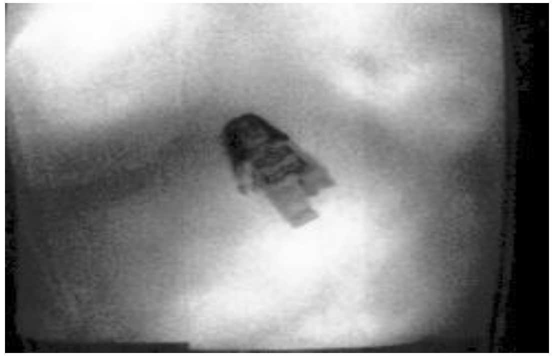
After CLAHE



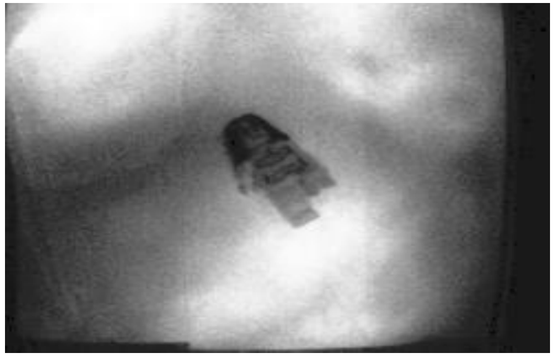
After MSR Gray

IMAGE	PREDICTIONS USING SOFTMAX FUNCTION	COMMENT
Original Image	Wonder Woman (**58%**)	True Prediction
After CLAHE	Wonder Woman (**85.67%**)	True Prediction
After MSR Gray	Wonder Woman (**94.318%**)	True Prediction

Image Processing Effects



After AHE



After Histogram Equalization

After MSR Color

IMAGE	PREDICTIONS USING SOFTMAX FUNCTION	COMMENT
After AHE	Batman (74%)	False Prediction
After Histogram	Batman(99.97%)	False Prediction
After MSR Color	Batman(100%)	False Prediction

Limitations

- Inability to automatically detect the illumination condition and enhance image.
- Inability to detect intruder severity.
- Over-fitting of the CNN model due to inadequate training data.

Future Enhancements

- Automatic image enhancement based on illumination condition.
- Intruder severity detection with weapon detection schemes using models like R-CNN.
- Creation and collection of enough dataset for optimum training.

Conclusion

- Knowledge in camera calibration was gained.
- Enhanced the images taken in inadequate lighting conditions.
- Built different CNN classification models.
- Learnt and implemented concept of Transfer Learning.
- Studied effects of enhancing images in classification accuracy.

References

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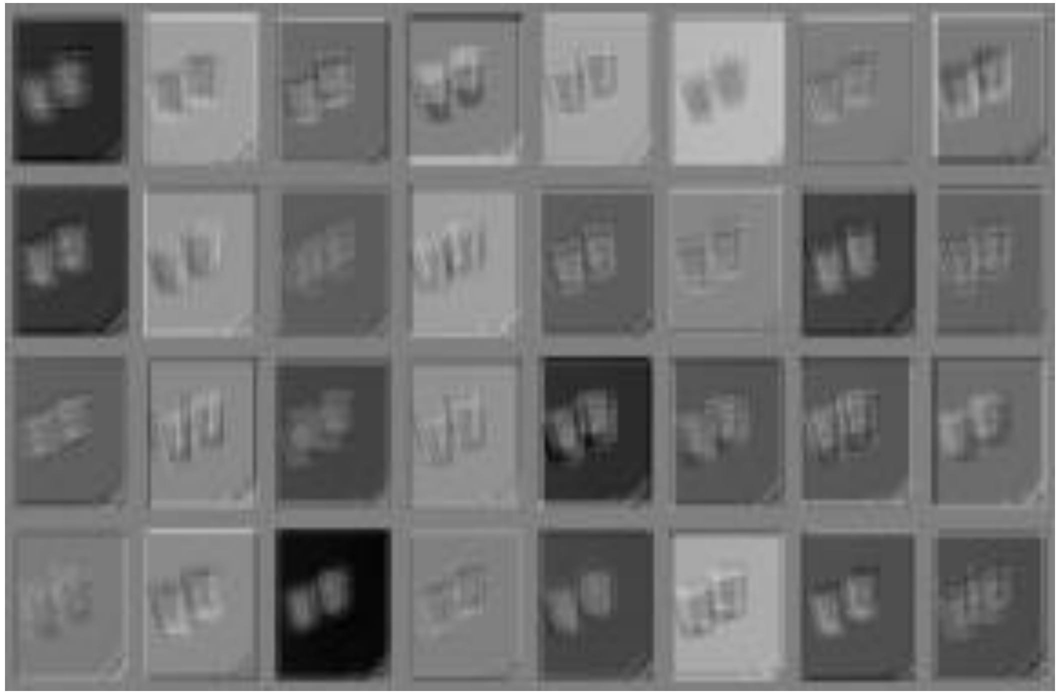
- A. Karpathy,“Standford University CS231n:” Convolutional Neural Networks for Visual Recognition.”

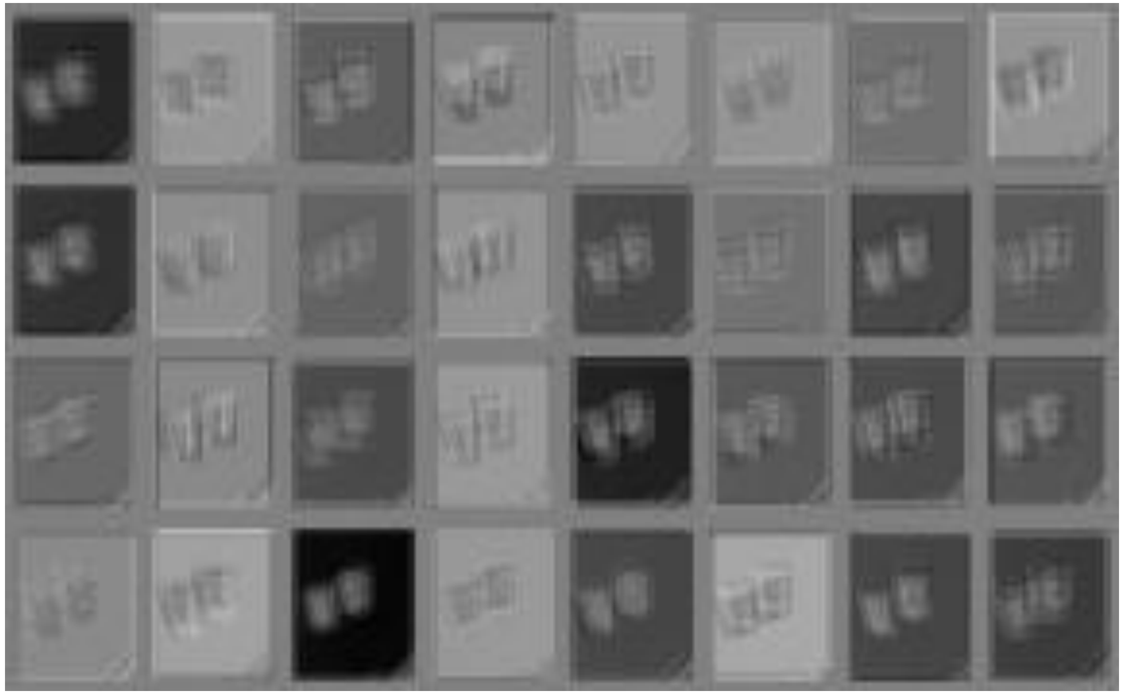
- C Szegedy, W Liu, Y Jia, P Sermanet, S Reed, D Anguelov, D Erhan, V Vanhoucke and A Rabinovich, “Going Deeper with Convolutions”, in *Computer Vision and Pattern Regonition (CPVR)*, 2015.

Thank You

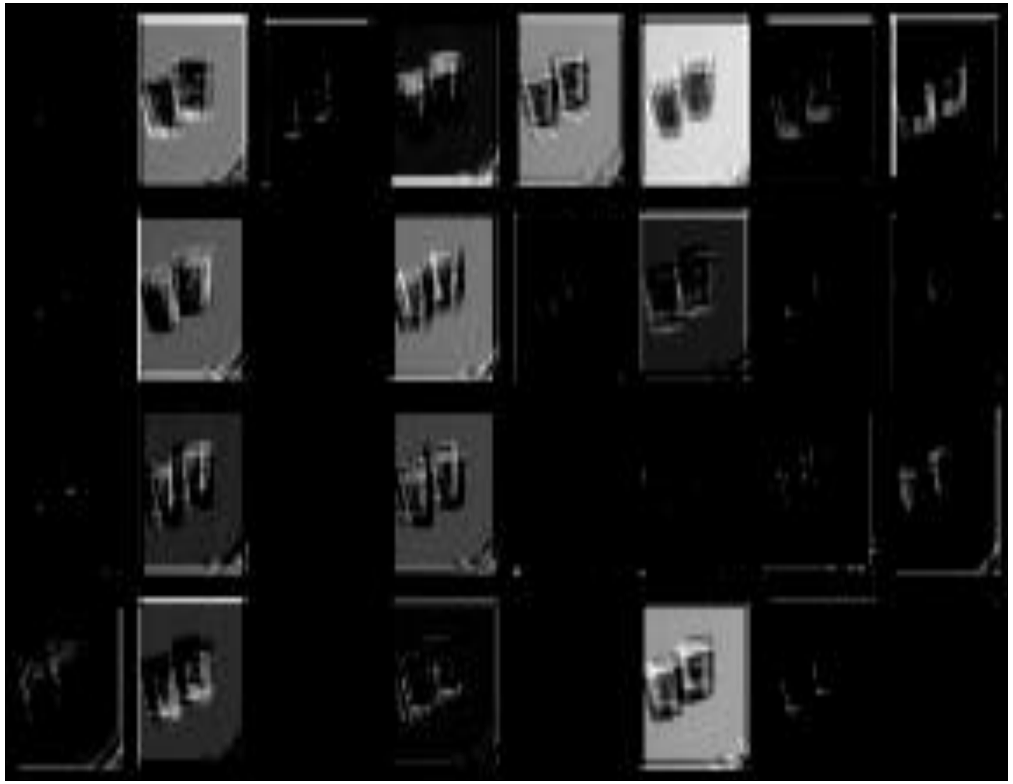
Backup section

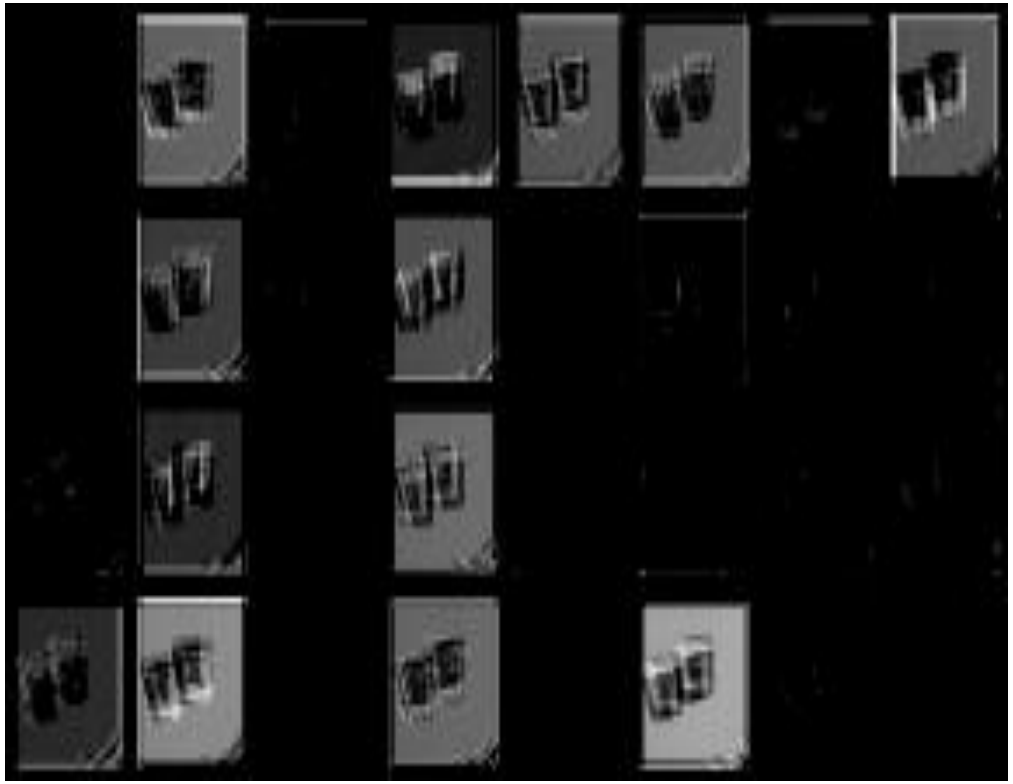
Features Extracted by Convolutional Layer



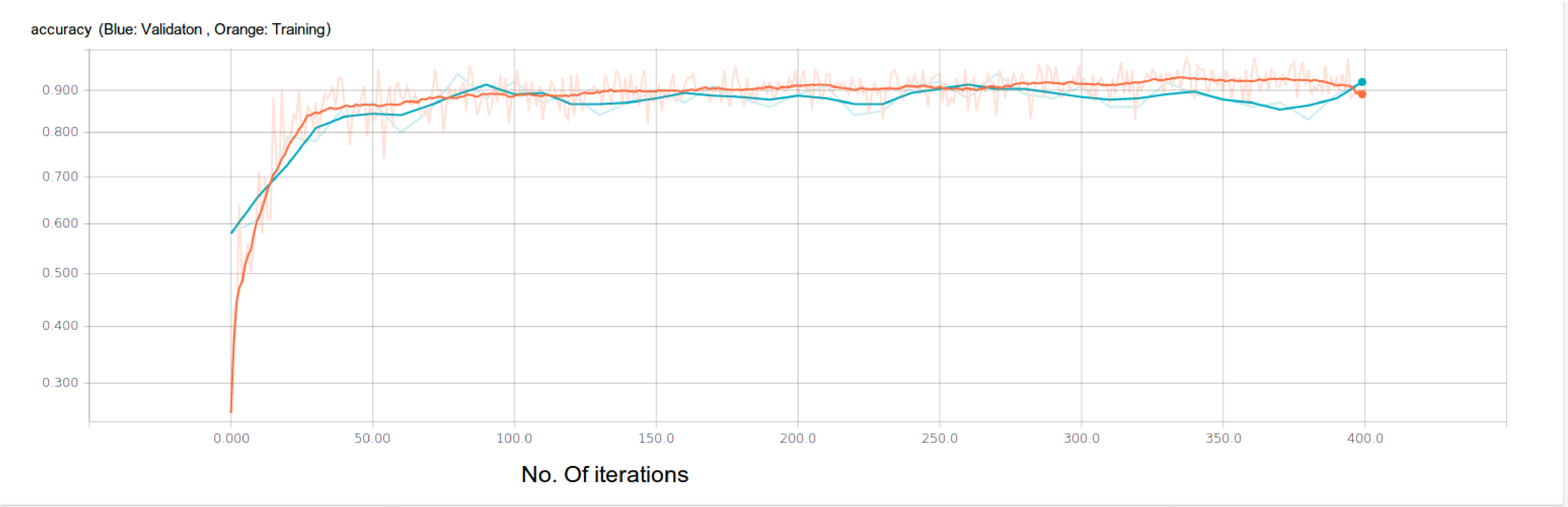


Features Extracted by Convolutional Layer

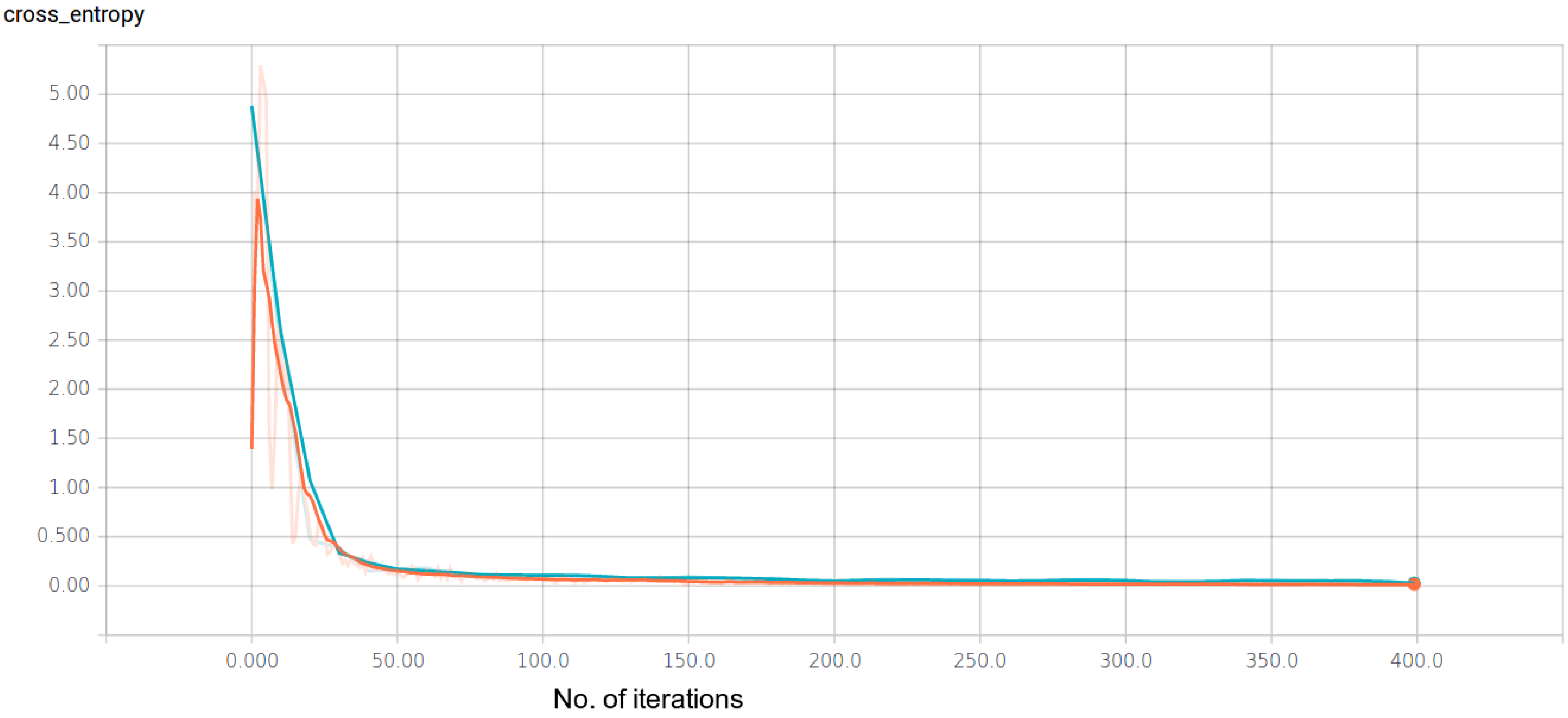




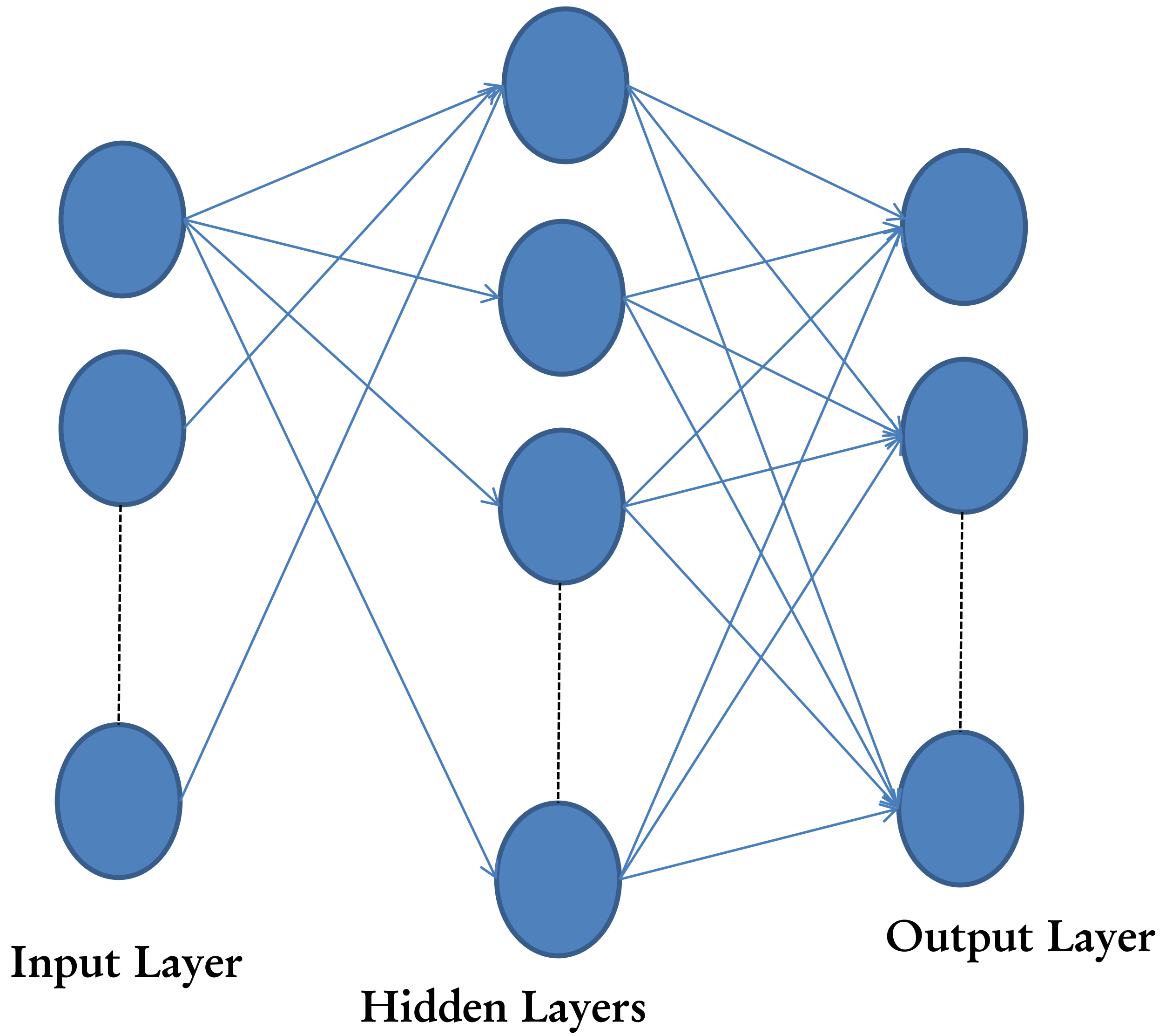
Transfer Learning Accuracy



Transfer Learning Cost Function



Self made Fully Connected Layer



For MNIST dataset:
28x28 input neurons
2 hidden layers (64x32)
Random weight initialization
Accuracy: 98%
Iteration 20000

For CIFAR dataset:
Feature extracted using Inception Model
1920 input neurons
2 hidden layers(128x32)
Random weight initialization
Accuracy : 66%
Iteration :70000