UAV Pose Estimation in Indoor Corridor Using Monocular Vision and Deep Learning

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Autonomous Navigation

- Devices are capable of riding itself by responding to the "Navigating Environment".
- Fully Programmed
- Generate Flight Command on their own

Autonomous Drone Navigation Scenario

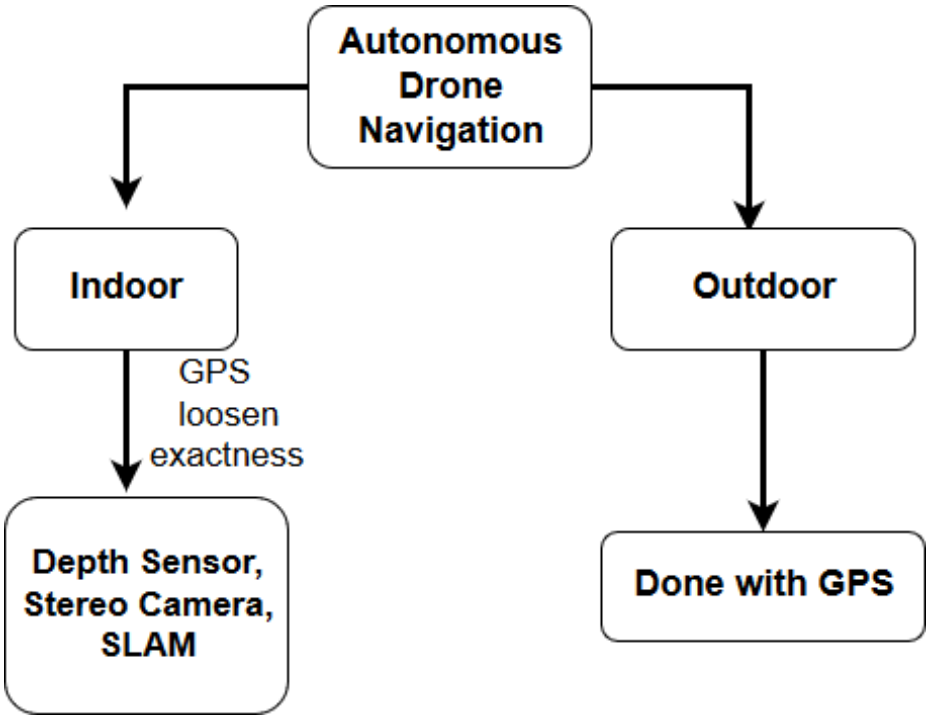


Figure 1: Autonomous Drone Navigation Scenario

Problem Domain

Autonomous Drone Navigation Scenario

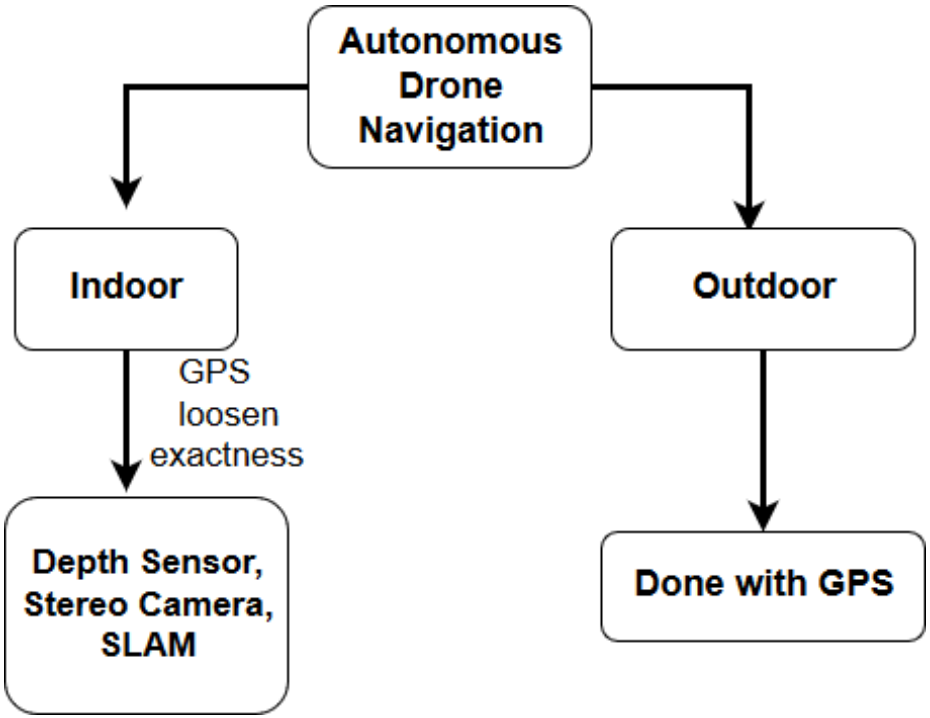


Figure 1: Autonomous Drone Navigation Scenario

Our Working Scenario

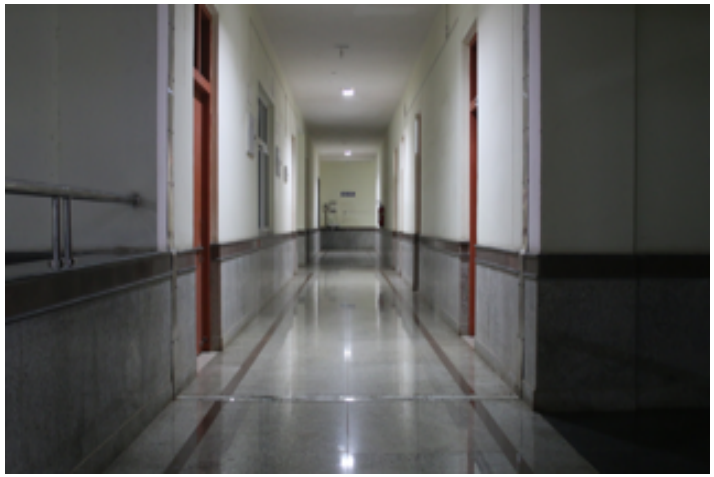


Figure 2: A Corridor in TIIR

Navigation is Modelled as " Regression Problem "

Problem Origin

Problem Origin

Problem Statement

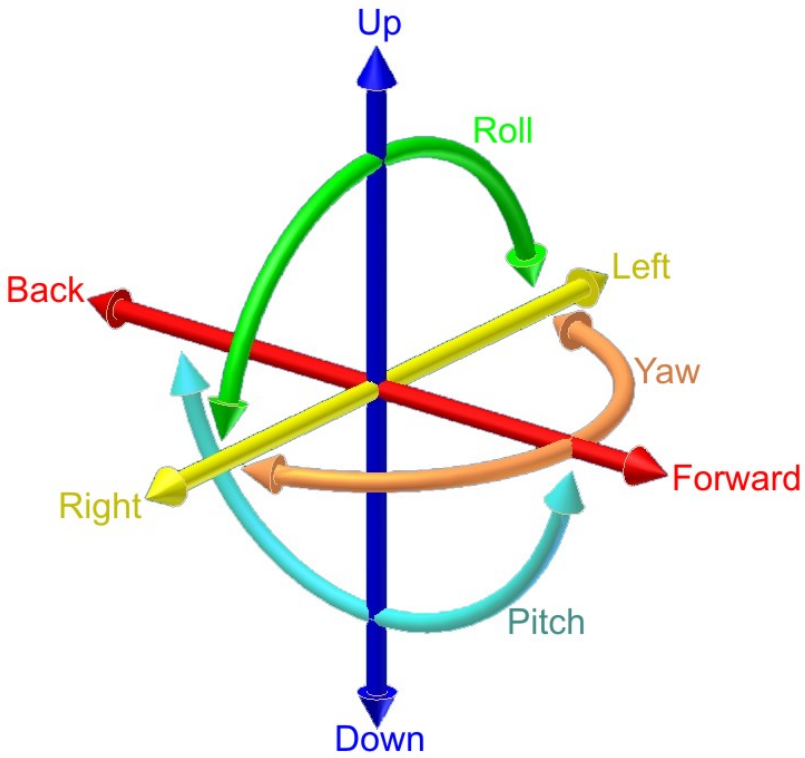


Figure 3: degrees of freedom

Problem Statement

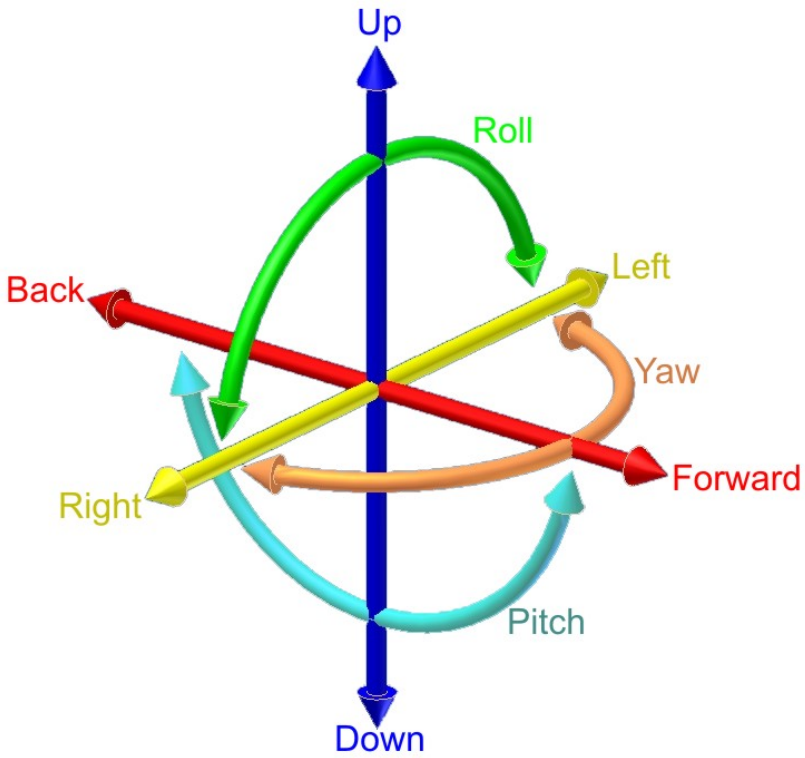
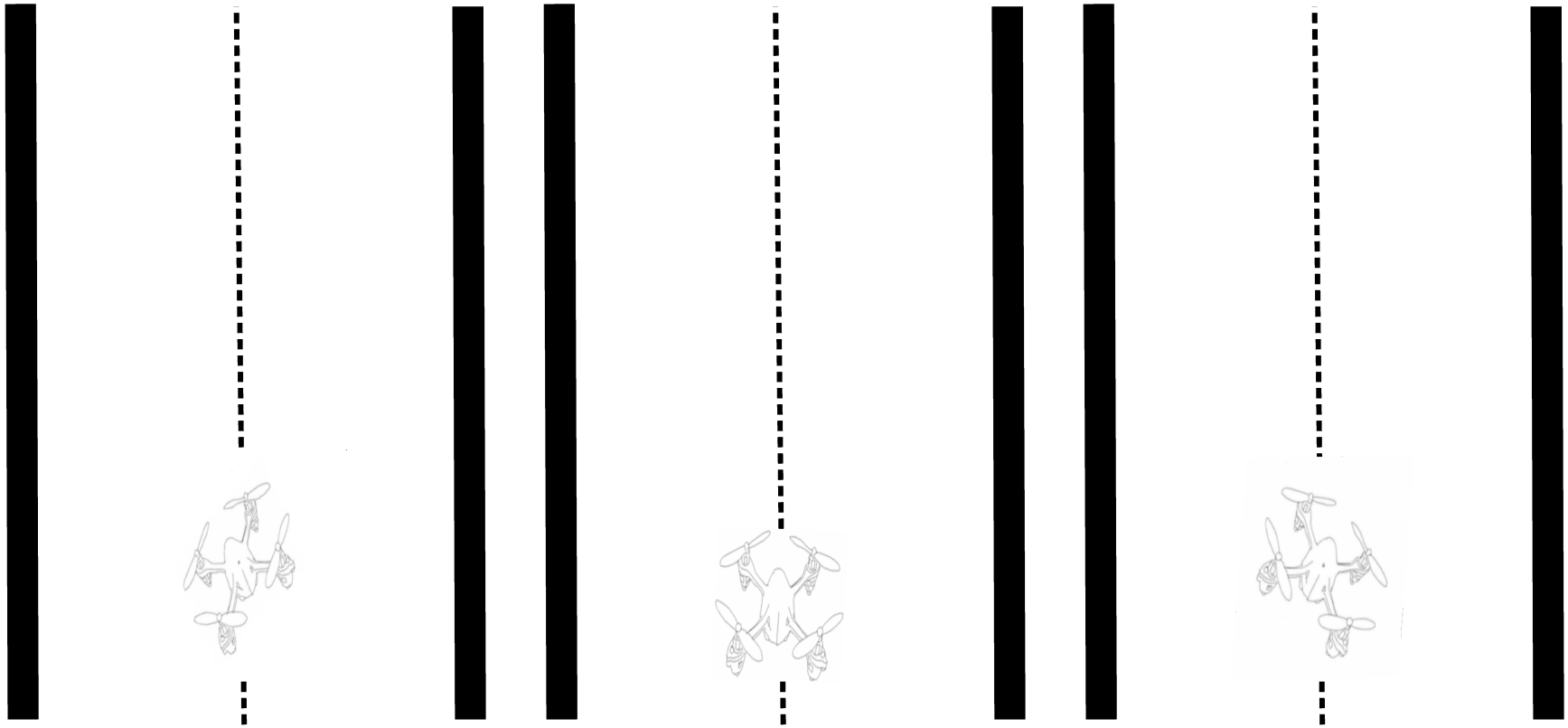


Figure 3: degrees of freedom

Drone pose correction in the indoor corridor environment such that device must always be facing straight when it is at the center of the transit environment using

"YAW FLIGHT COMMAND"

Problem Scenario



Challenges to Drone Navigation/Localization

- Payload
- Power
- Degrees of Freedom
- Stability

Literature Survey

Our Related Study Falls into any of the following

1. **Range Sensor based Navigation** $\rightarrow$ Depth Information

Literature Survey

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1. **Range Sensor based Navigation** $\rightarrow$ Depth Information
2. **SLAM based Navigation** $\rightarrow$ 3D Map Generation and Simultaneous Mapping

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Literature Survey

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3. **Stereo Vision based Navigation** → Two Lens
4. **Navigation With Learning based Algorithm** → Classification of Follow Command

Literature Survey

Our Related Study Falls into any of the following

1. **Range Sensor based Navigation** → Depth Information
2. **SLAM based Navigation** → 3D Map Generation and Simultaneous Mapping
3. **Stereo Vision based Navigation** → Two Lens
4. **Navigation With Learning based Algorithm** → Classification of Follow Command
5. **Deep Learning**

Literature Survey Cont.

- **ALVINN(NIPS, 1989)**
  - For land vehicle
  - 3-layer neural network
  - 99% accuracy

- **Quadrotor using Minimal Sensing For Autonomous Indoor Flight.(EMAV, 2007)**
  - one ultrasonic sensor and four infra-red sensors.
  - fully autonomous flight
  - most of publicly available quadcopters doesn't have infra red sensor.

Literature Survey Cont.

- **AlexNET(NIPS, 2012)**
  - Reduced Top-5 Error from 26.2% to 15.4%
  - 5 Convolutional Layer and 3 Fully Connected layers
  - Extensive Data Augmentation

- **Monocular Vision Slam for Indoor Aerial Vehicles(JECE, 2013)**
  - Used Monocular Camera
  - computationally expensive due to the 3-D reconstruction

Literature Survey Cont.

- **ZFNet(ECCV, 2013)**
  - Fine-Tuning of Alexnet
  - Developed a visualization technique named Deconvolutional Network

- **VGGNet(arXiv, 2014)**
  - Used only 3x3 filters
  - Decrease Spatial dim. but increase depth of the feature.

Literature Survey Cont.

- **InceptionNet(CVPR, 2015)**
  - Parallel convolutions
  - no fully connected layer
  - First model to Concatenate the outputs

- **Deep Neural Network for Real-Time Autonomous Indoor Navigation (arXiv, 2015)**
  - Used classification for flight command
  - No tilted case considered

Literature Survey cont...

- **ResNet(CVPR, 2016)**
  - Came up with the concept of Residual Block
  - Gradient flow is easy

- **DenseNet(CVPR, 2017)**
  - dynamic model which connect every layer with all of its previous layer
  - Fast Gradient Update

Research Motivation

- Weak strength of GPS[1] signal in indoor environment.
- Existing methods require much hardwares and software dependencies.
- Lacking Pilot's View

Objectives

- **Corridor Mid-Point Estimation**
- **Drone Alignment Estimate**

Best Case for Navigation

Proposed Scheme

AT MIDDLE OF THE CORRIDOR

FACING STRAIGHT

Flight Command → MOVE FORWARD

Proposed Scheme Cont.

AT MIDDLE OF THE CORRIDOR

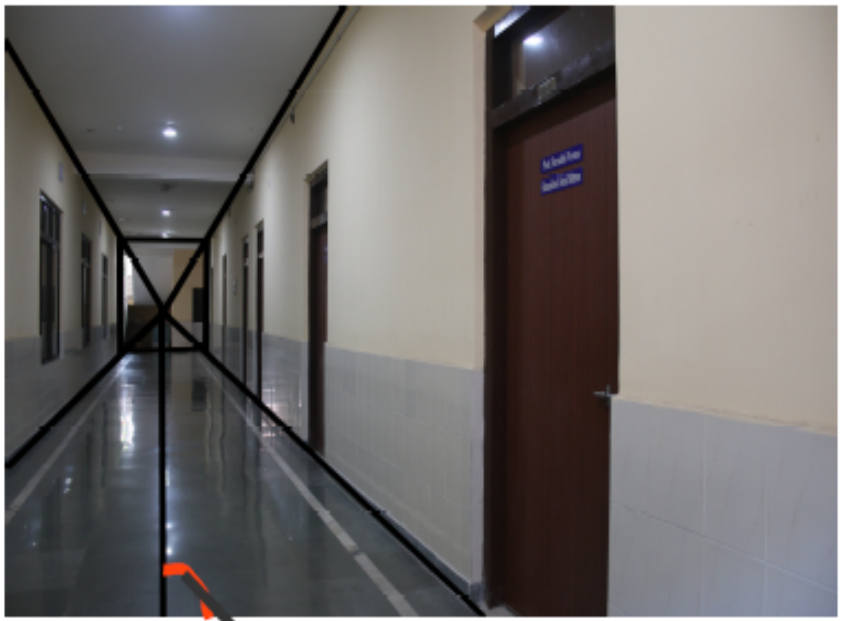
TILTED TOWARD LEFT

Flight Command → YAW RIGHT

Proposed Scheme Cont.

AT MIDDLE OF THE CORRIDOR

TILTED TOWARD RIGHT



Flight Command → YAW LEFT

Localization Algorithm

Algorithm 1: TiltPose →returns pose of the drone

Input: **IMAGE** taken from the onboard camera

Result: flight command to localize st drone always face stright

```
1 d=DistFind(IMAGE)
2 if (d < image.width/2 − 20) then
3 |   return tilted right;
4 else if (d > image.width/2 + 20) then
5 |   return tilted left;
6 else
7 |   return facing straight;
8 |   ;
```

Localization Algorithm

Algorithm 2: DistFind →Distance of point of intersection between the Bisector and Horizontal Axis

Input: **IMAGE** of the the transit environment from Algorithm Tilt-Pose

Result: number of pixels betwwen bottomleft pixel of the image and the intersection point

1 Normalize pixel value of **IMAGE** between 0 to 1;
2 RGB to BGR conversion;
3 Normalize **IMAGE** with mean and standard deviation of ImageNet-10000[2] data set;
4 DistPix = Trained_Model(**IMAGE**);
5 **return** DistPix;

Deep Learning as Solution

- Deep learning class ConvNet[3] enable direct feature extraction over images.
- We learn intrinsic features of the image captured from drone camera to guide pose correction.

Data Set Creation

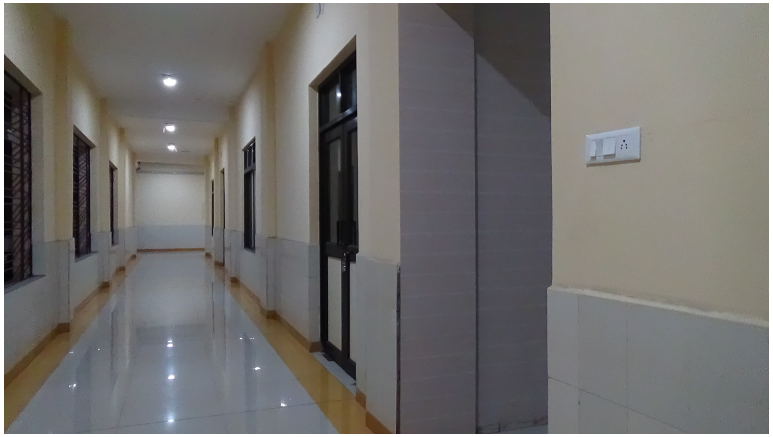
- **107 Corridor** $\rightarrow$ NIT Premises

- **DataSet Size** $\rightarrow$ **65000**
  - 21000 Training Set Image
  - 300 Test Set Image

Data Set Creation (Raw Data)

(a) At Center aligned to Left

(b) At Center aligned to Center



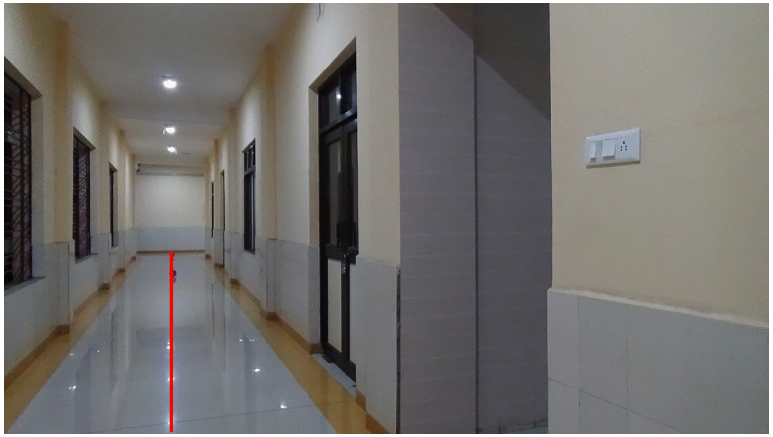
(c) At Center aligned to Right

Figure 4: various instances of indoor corridor captured from onboard

Data Set Creation (Labelled Data) (Cont.)

(a) At Center aligned to Left

(b) At Center aligned to Center



(c) At Center aligned to Right

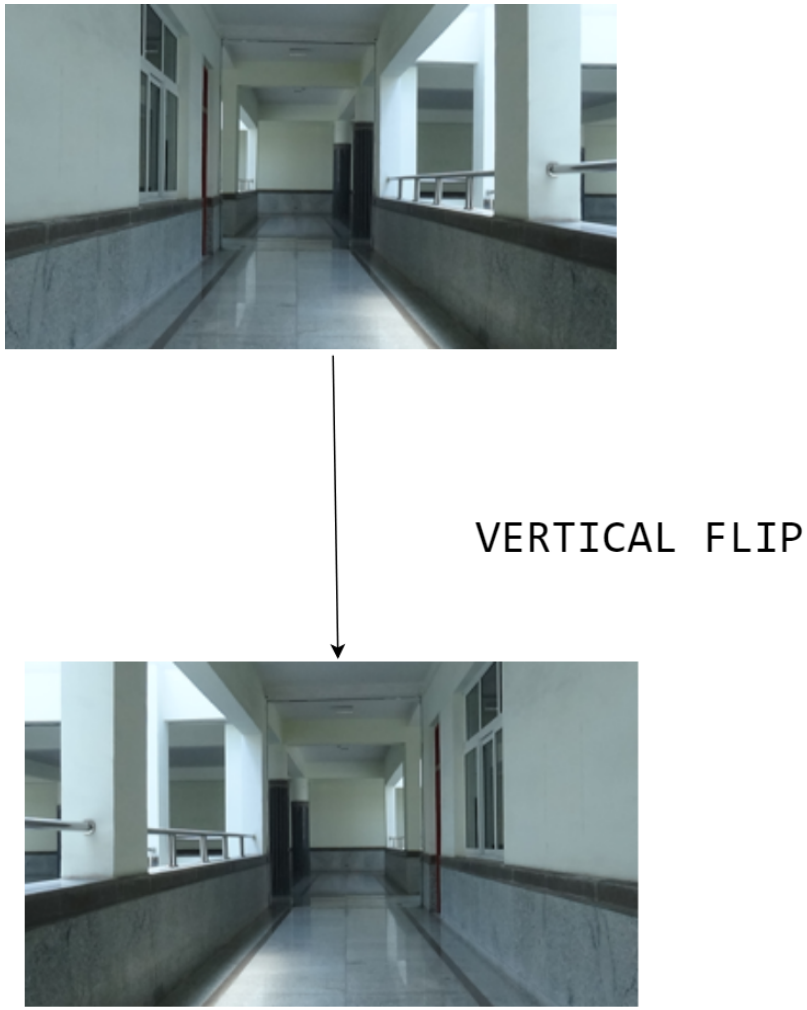
Figure 5: labelled images used to find ground truth

Data Set Samples

Figure 6: various instances of indoor corridors

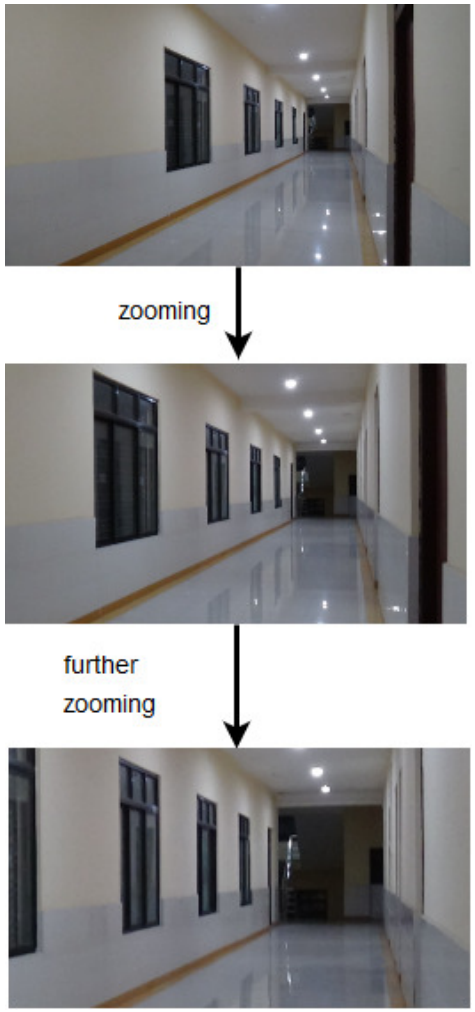
Data Augmentation Technique

- Image Flipping



Data Augmentation Technique (Cont.)

- Image Zooming



CNN Architecture

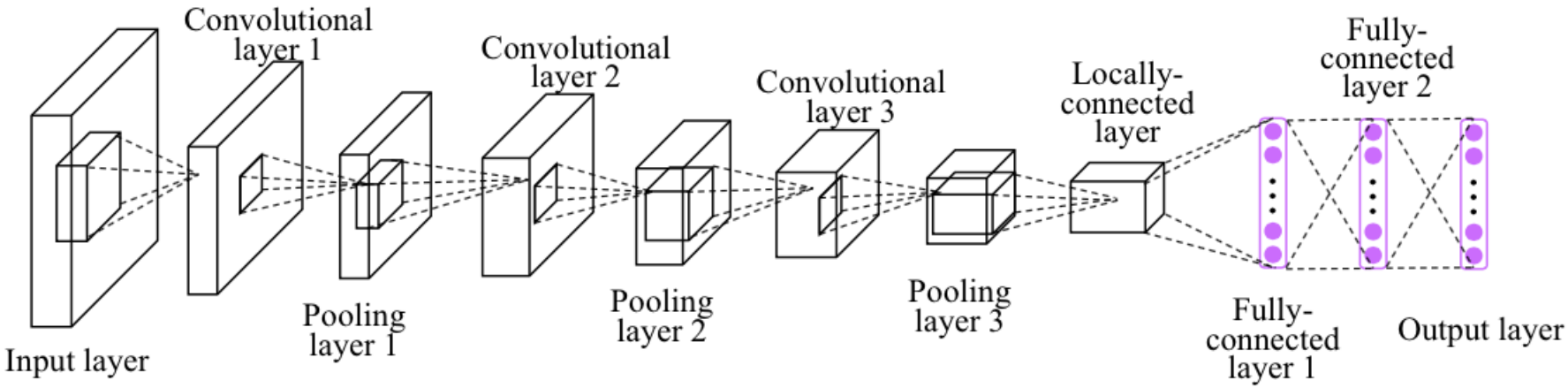


Figure 7: Convolutional Neural Network

CNN Architecture cont..

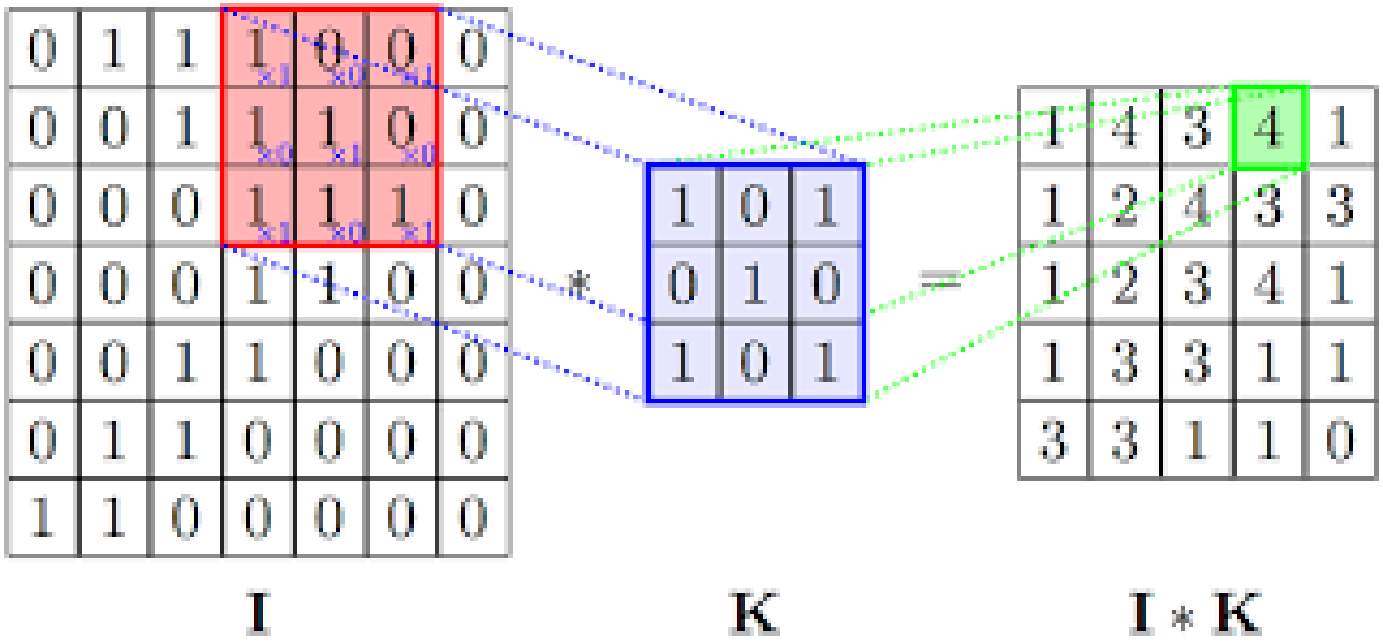
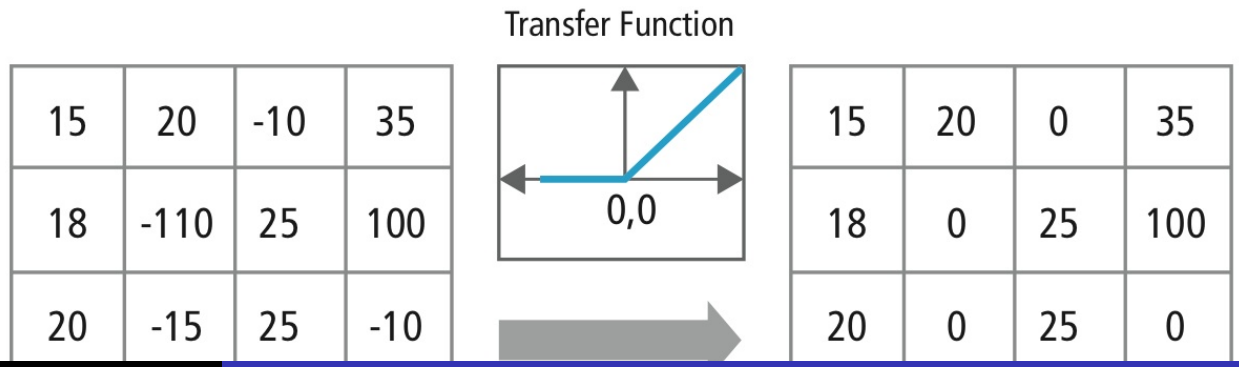


Figure 8: Convolutional Layer



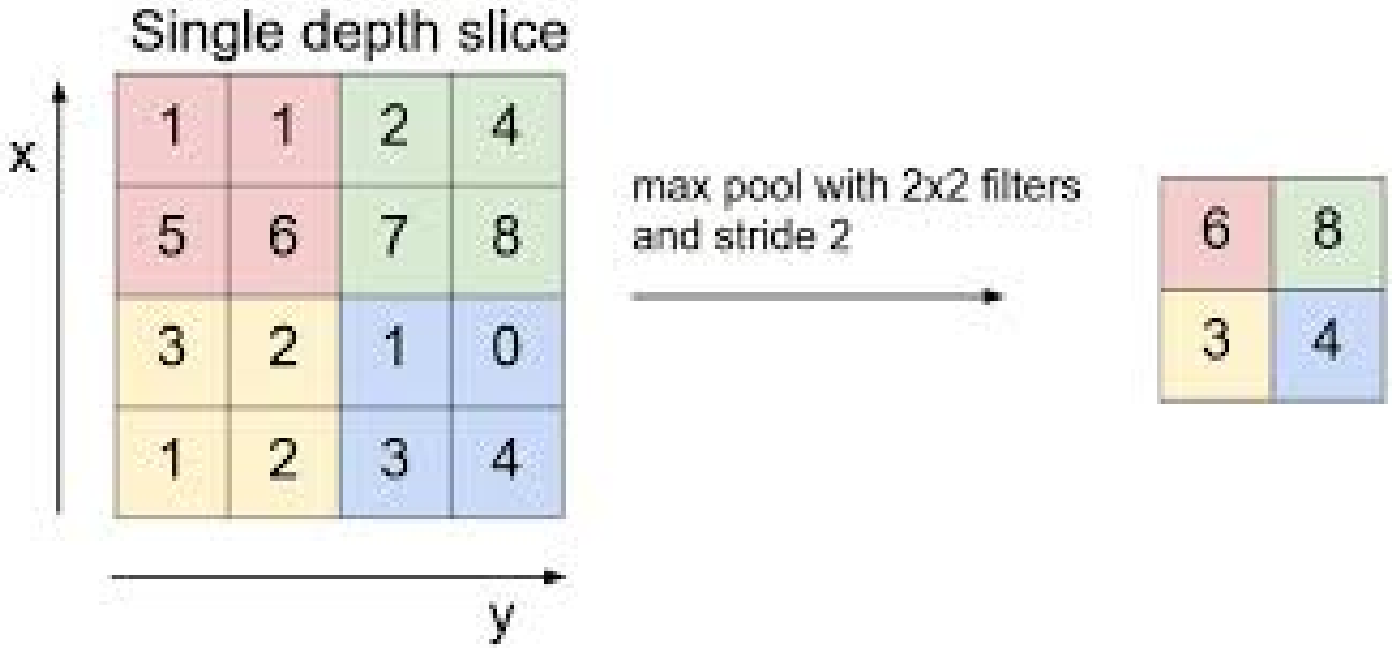


Figure 10: Pooling Layer

Working Model

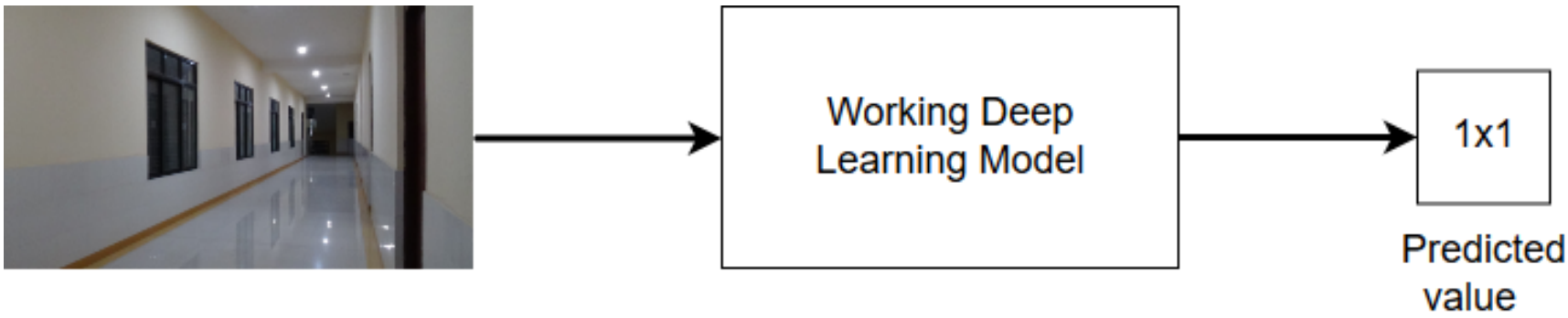


Figure 11: fig explains the working model

Architecture of Working Model

Deep Model Architecture Used			
Pre-Trained Model	**Augmented Layers**	**Output Layer**	**Output**
ALEXNET	-	FC(4096,1)	(1,1)
DenseNet-161	CONV2D(2208,1024,1) CONV2D(1024,128,5) CONV2D(128,16,1)	FC(96,1)	(1,1)
DenseNet-201	CONV2D (1920,1024,1) CONV2D(1024,128,5) CONV2D(128,16,1)	FC (96,1)	(1,1)
INCEPTION-V3	**Main**:CONV2D (1920,1024,1) CONV2D(1024,128,5) CONV2D(128,16,1) **AUX**:CONV2D (768,128,4) CONV2D(128,32,2) CONV2D(128,16,(1,2))	FC (256,1) FC (640,1)	(1,1) (1,1)

Architecture of Working Model Cont...

Pre-Trained Model	**Augmented Layers**	**Output Layer**	**Output**
ResNet-50	CONV2D(2048,1024,1) CONV2D(1024,128,5) CONV2D(128,8,1)	FC(96,1)	(1,1)
ResNet-101	CONV2D(2048,1024,1) CONV2D(1024,128,5) CONV2D(128,8,1)	FC(96,1)	(1,1)
ResNet-152	CONV2D(2048,1024,1) CONV2D(1024,128,5) CONV2D(128,8,1)	FC(96,1)	(1,1)

Training Of Models

- We use Mean Absolute Error function to learn model listed above.

$$Mean\ Absolute\ Error(\hat{y}, y) = \frac{1}{n}\sum_{t=1}^{n}|\hat{y}_t - y_t|$$

Here,
$\hat{y}$ is the prediction made on all the training examples
y is ground truth value of all the examples of training set.
$\hat{y}_t$ is the prediction made on t^{th} training example
y_t is ground truth value of t^{th} training set.
n is the batch size.

Convergence Graph for Alexnet

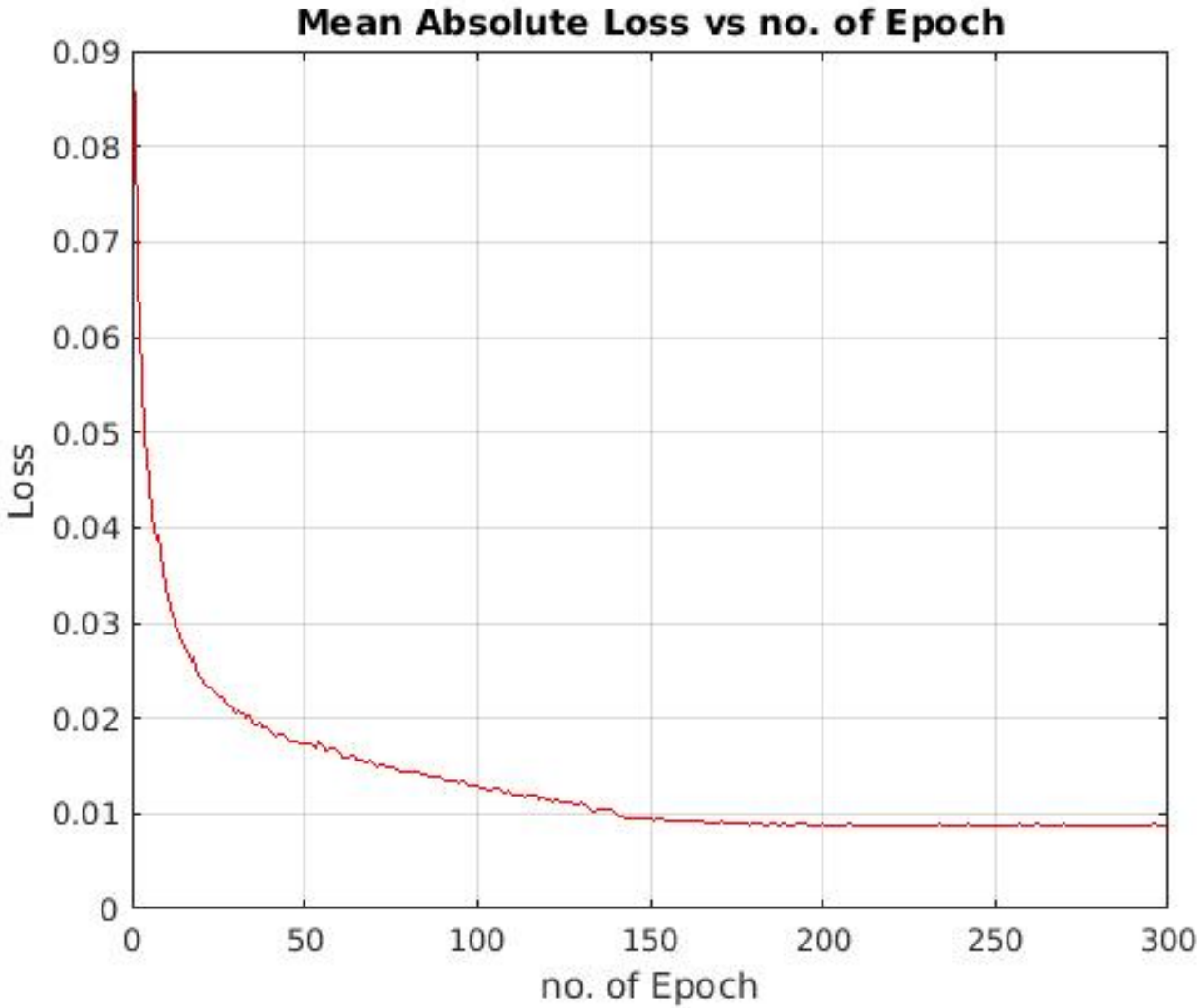


Figure 12: Trianing Loss vs No. of Epoch for MAE for Alexnet

Convergence Graph for DensNet-161

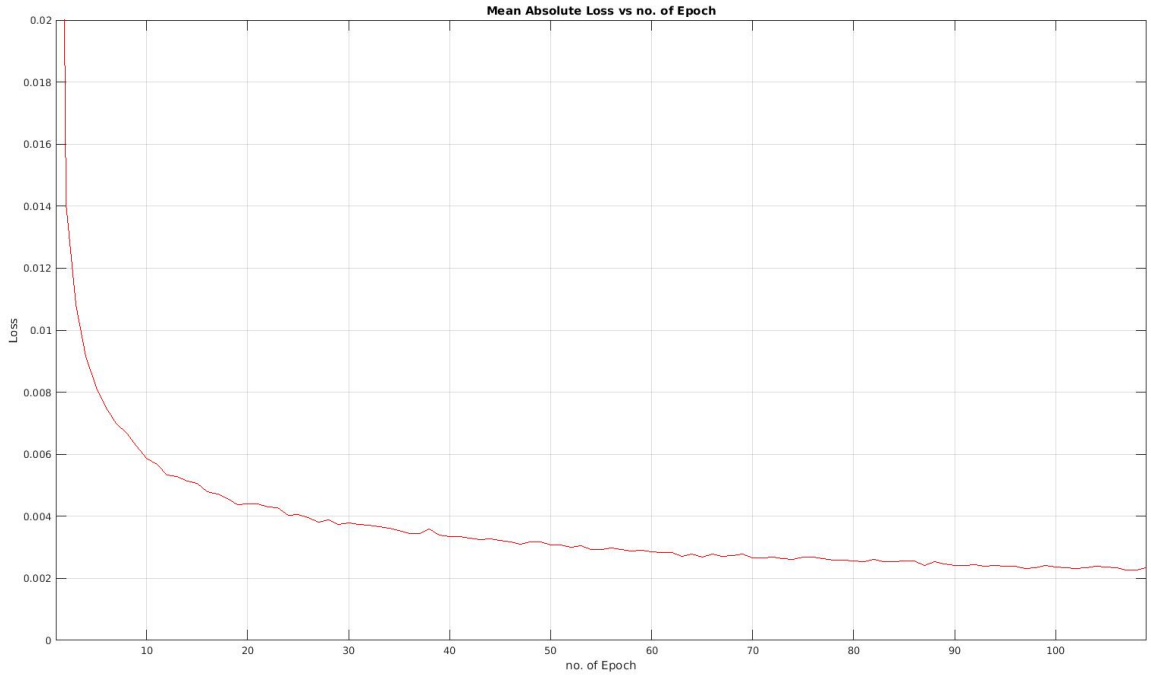


Figure 13: Trianing Loss vs No. of Epoch for MAE for DensNet-161

Convergence Graph for DensNet-201

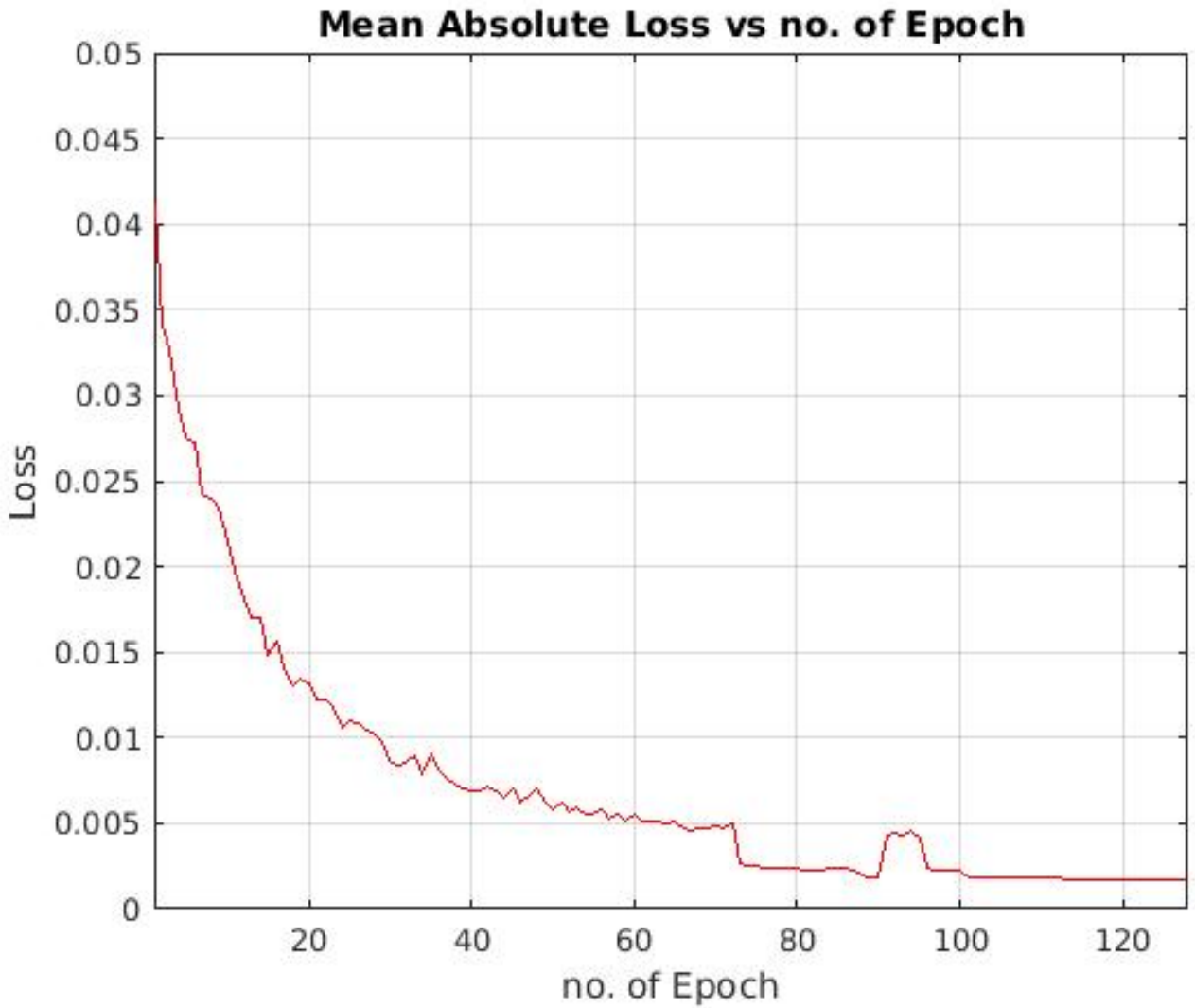


Figure 14: Trianing Loss vs No. of Epoch for MAE for DensNet-201

Convergence Graph for Inception-V3

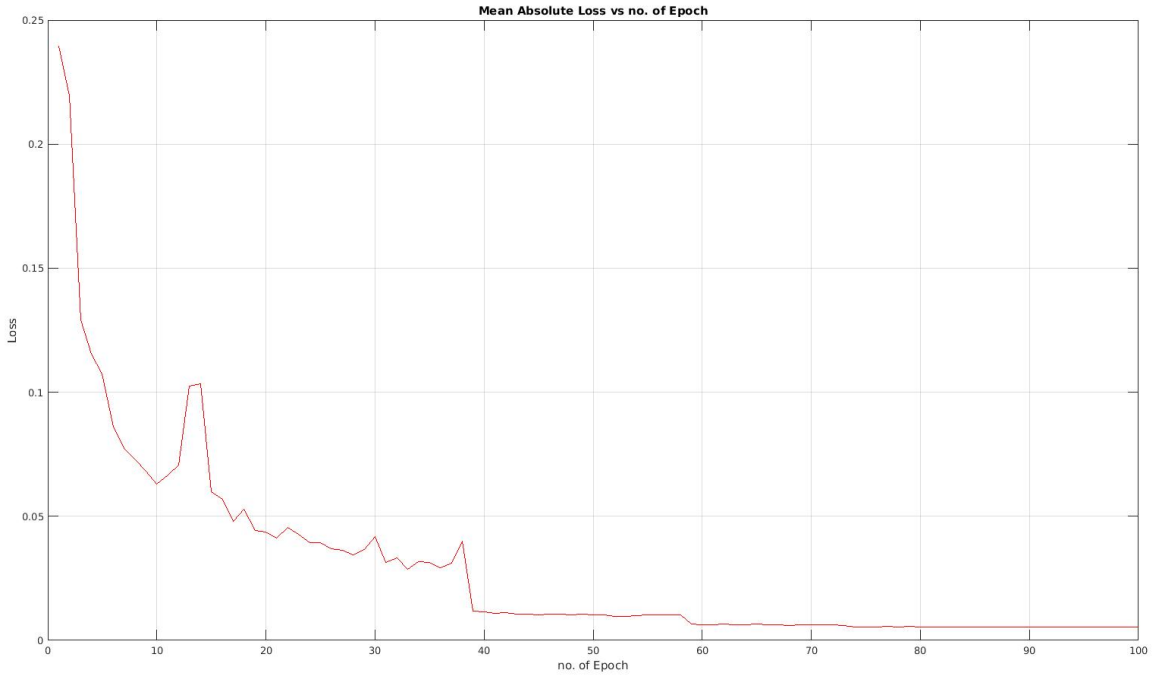


Figure 15: Trianing Loss vs No. of Epoch for MAE for Inception-V3

Convergence Graph for ResNet-50

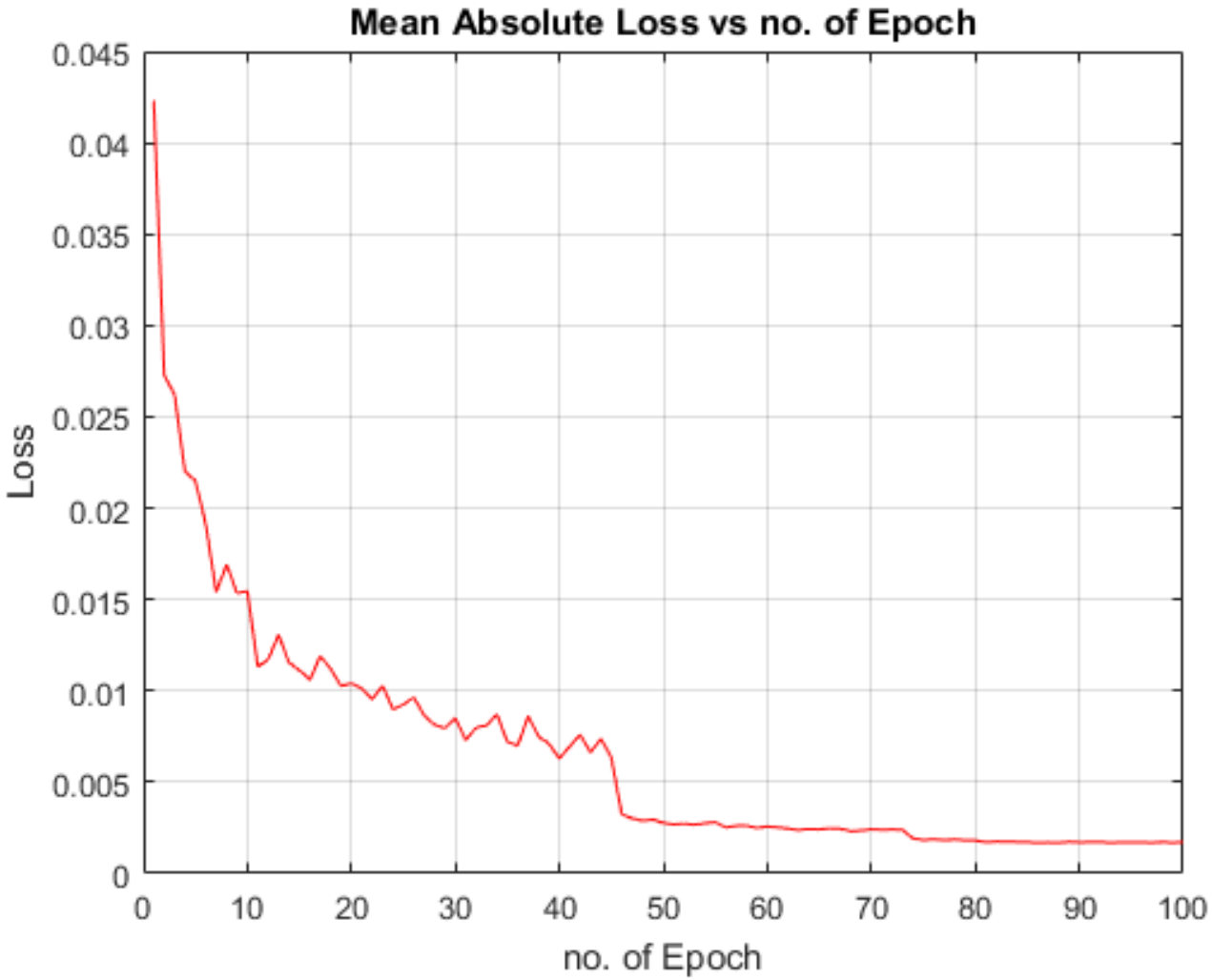


Figure 16: Trianing Loss vs No. of Epoch for MAE for ResNet-50

Convergence Graph for ResNet-101

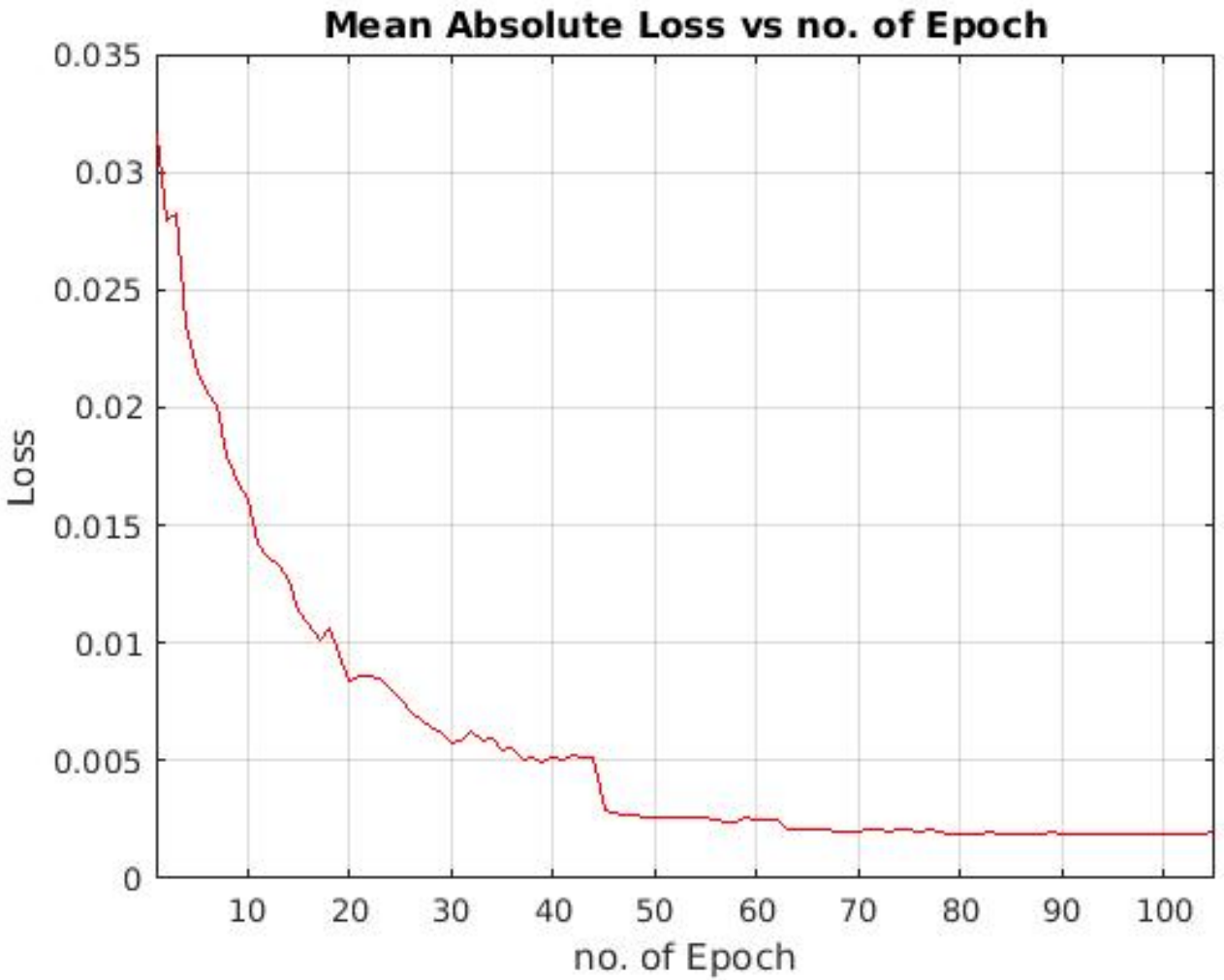


Figure 17: Trianing Loss vs No. of Epoch for MAE for ResNet-101

Convergence Graph for ResNet-201

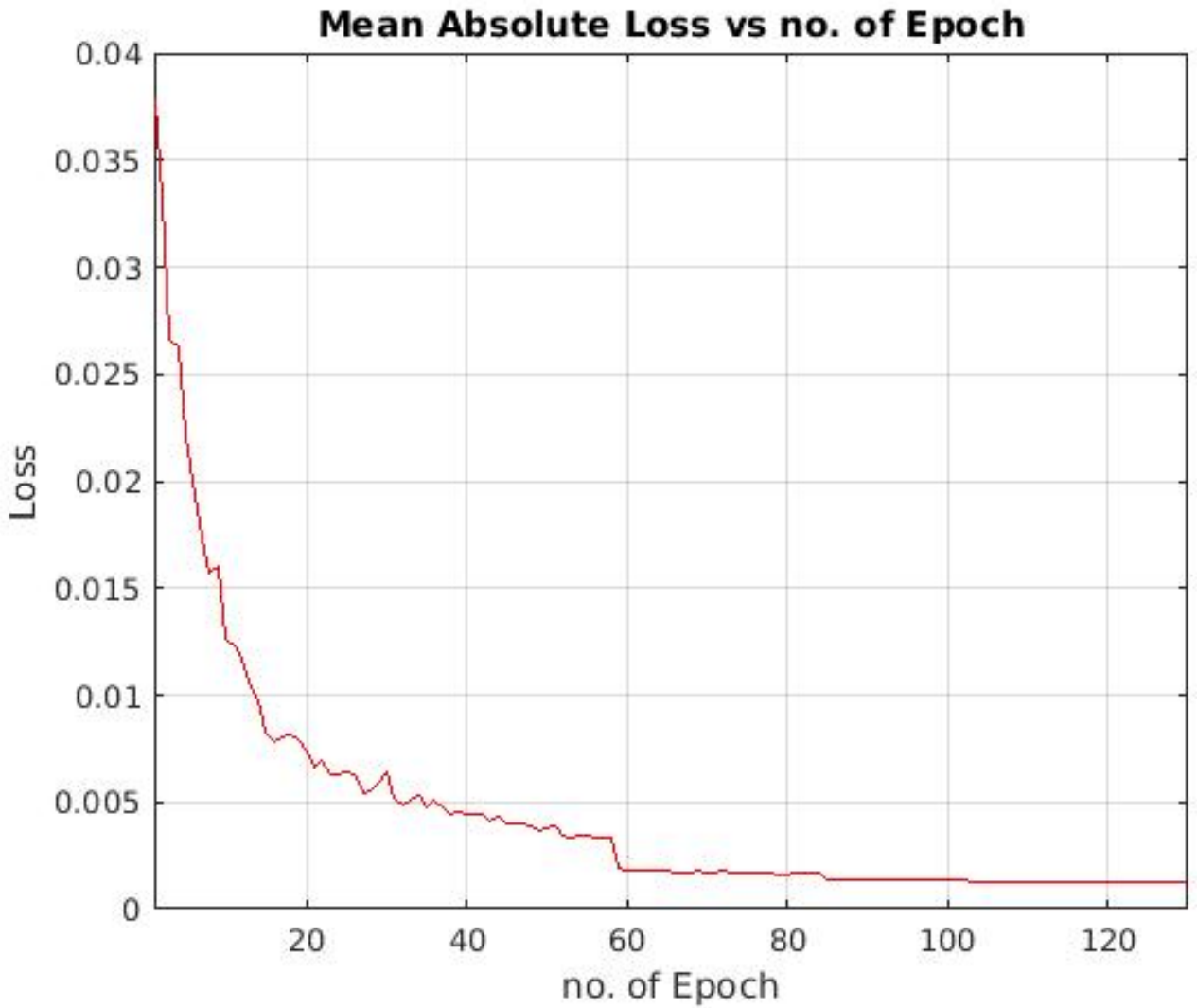


Figure 18: Trianing Loss vs No. of Epoch for MAE for ResNet-201

Testing Metrics

- We used three different metric to evalute the trained Model performance on test set, defined below

$$Mean\ Square\ Error(\hat{y}, y) = \frac{1}{n}\sum_{t=1}^{n}(\hat{y}_t - y_t)^2$$

$$Mean\ Absolute\ Error(\hat{y}, y) = \frac{1}{n}\sum_{t=1}^{n}|\hat{y}_t - y_t|$$

$$Mean\ Relative\ Error(\hat{y}, y) = \frac{1}{n}\sum_{t=1}^{n}\frac{|\hat{y}_t - y_t|}{y_t}$$

Here,
$\hat{y}$ is the prediction made on all the test examples
y is ground truth value of all the examples of test set.
$\hat{y}_t$ is the prediction made on t^{th} test example
y_t is ground truth value of t^{th} test set.
n is the total number of test example.

Performance over Test Set

Model Accuracy for Distance Prediction (in pixel)			
Model Name	**Mean Square Error**	**Mean Absolute Error**	**Mean Relative Error**
AlexNet	5.5677	27.0064	54.1467
DenseNet-161	0.0326	2.5060	1.557
DenseNet-201	0.0828	3.6442	12.1421
Inception-V3	0.0687	3.1364	10.4852
ResNet-50	0.0473	2.7485	9.0729
ResNet-101	0.1186	4.2163	14.6806
ResNet-201	0.06617	3.4258	10.8230

Table 1: Error in Distance Predicted

Distance Estimation by DenseNet-161 on Test Images

Model Performance When Drone tilted Right				
Images	**Ground Truth**	**Predicted Value**	**Abs. Diff**	**Location**
	**53.6**	**52.17**	**1.42**	CS-Dept
	**44**	**48.13**	**4.13**	TIIR

Result Cont...

Model Performance When Drone Facing Straight				
Images	Ground Truth	Predicted Value	Abs. Diff	Location
	174.93	169.01	5.91	Main Building
	156.2	157.84	1.581	TIIR

Result Cont...

Model Performance When Drone tilted Left				
Images	Ground Truth	Predicted Value	Abs. Diff	Location
	257.6	258.7	1.1725	Physics Dept
	262.39	266.31	3.912	TIIR

Conclusion

We summarize as follows :

- We performed **Pose Estimation**, one **Parameter** for **Localization** by modelling it to a **REGRESSION** task.
- This task is attained by distance calculated from the image captured from **Monocular Camera** with the help of pre-trained deep learning model.
- We have taken into consideration the Pilot perspective of ride, far novel than machine dominated navigation approach.

Future Work

We can formalize future work as follows:

- To propose a stopping condition i.e. Landing of the drone.
- To propose method to navigate in curvy corridor.
- To include more extreme condition and more building to enhance dataset .

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Thank you!