

Traffic Signs Detection and Recognition System (TSDR)

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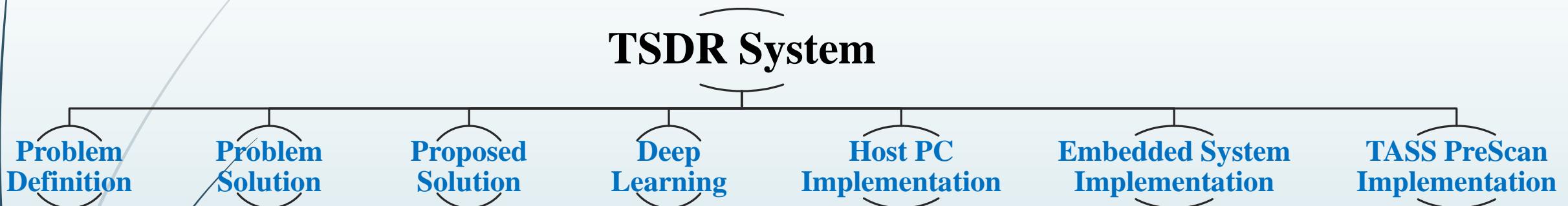


Under the appreciated supervision of

Dr. Maher Mansour

Eng. Kerolos Karam and Dr. Magdy El-Morsy from Mentor Graphics

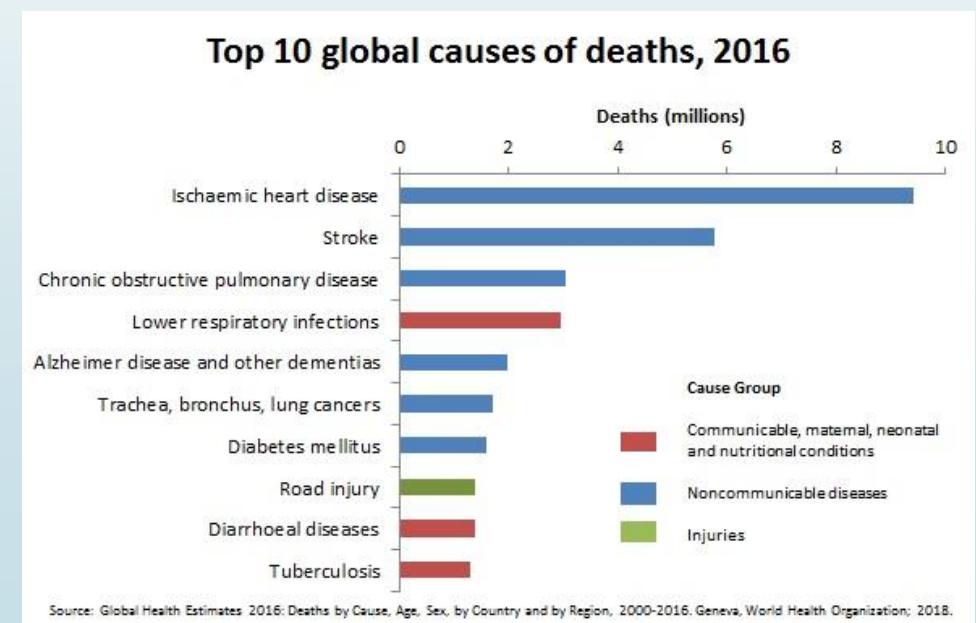
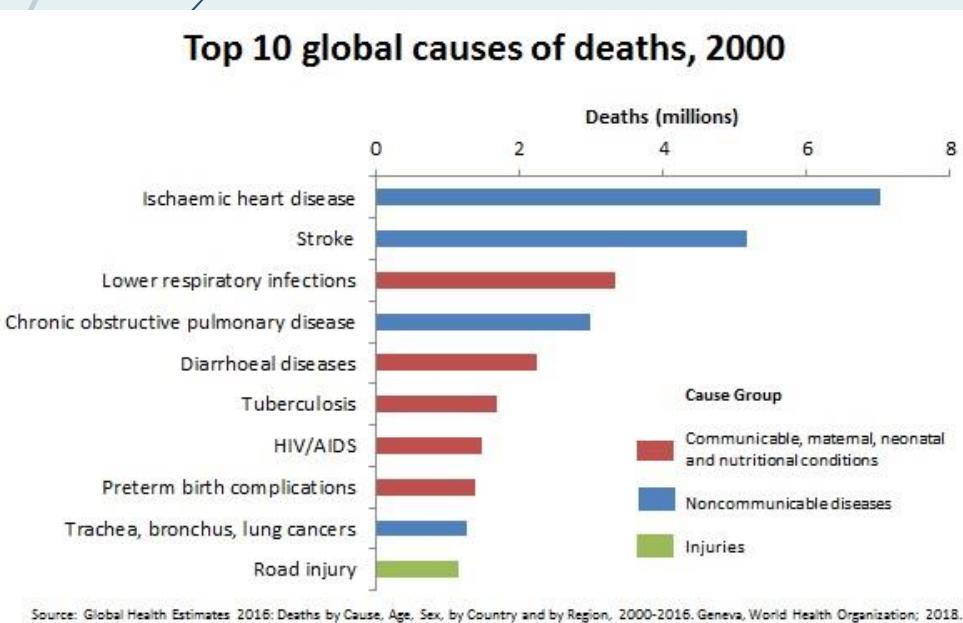
Contents



Problem Definition

Problem Definition – Road Accidents

- Around the world, more than 1.3 million people die every year in car crashes (including about 1,500 children under the age of 15) while another 50 million people are injured. [1]
- In fact, car crashes are the 8th leading cause of death in the world in 2016 [2].



Statistic by the World Health Organization shows that road accidents are 8th leading cause of death around the world in 2016 after being the 10th in 2000!

Problem Causes

Complex real-life situations

- ▶ **Lighting conditions** are changeable
- ▶ **The presence of other objects** in the scene
- ▶ **Visibility angle** and position in the image.
- ▶ **The long exposure to the sunlight**, color of traffic signs often gradually fades.
- ▶ If the image is acquired from a moving car, then it often suffers from **motion blur** and car vibration.



Lighting conditions



Presence of objects



Viewing angles



Exposure to sunlight

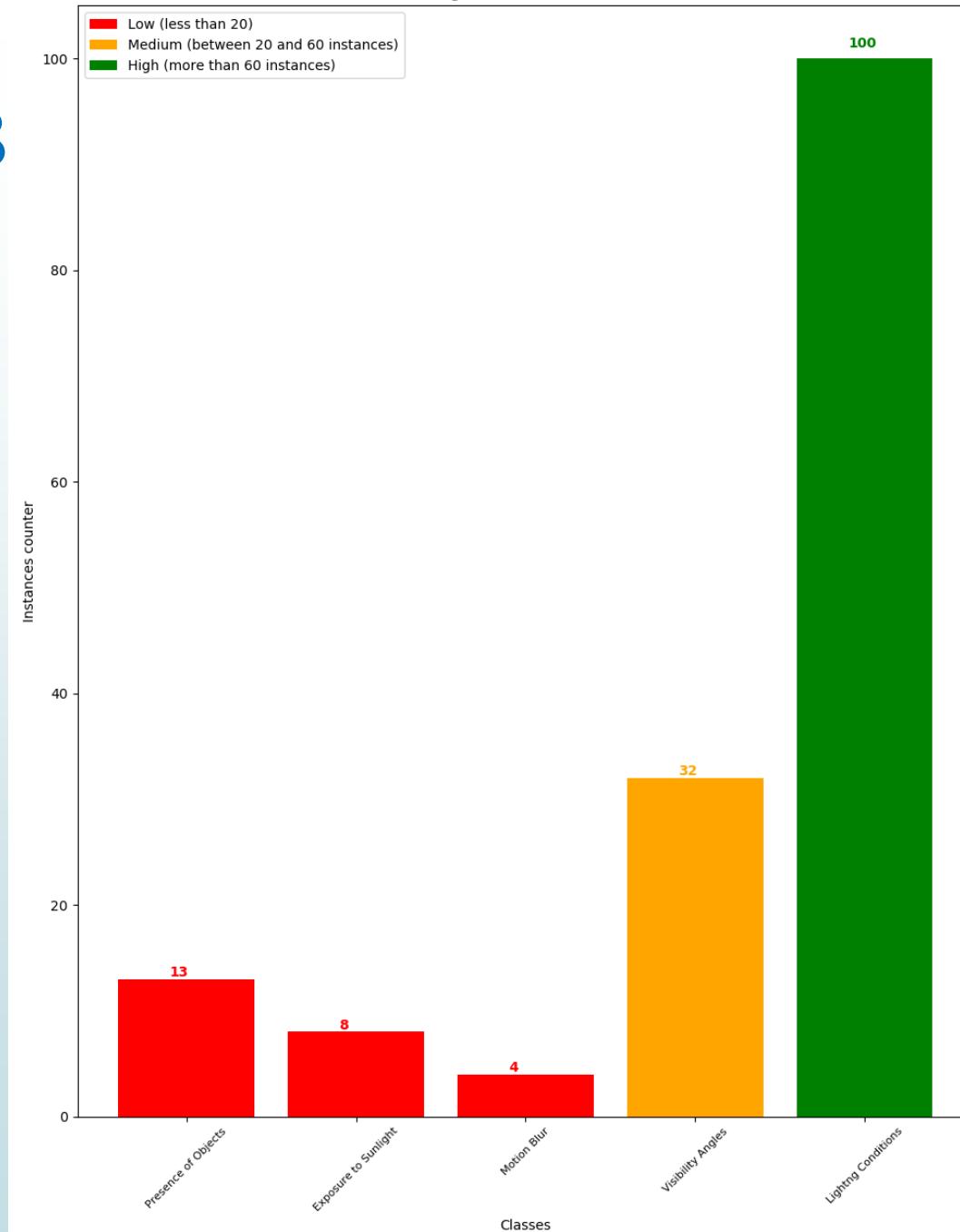


Motion blur

Problem Causes in GTSDB

Presence of the aforementioned traffic signs difficulties in the *German Traffic Signs Detection Benchmark* (GTSDB)

| Problem | Number of instances |
|----------------------|---------------------|
| Lighting Conditions | 100 |
| Visibility Angles | 32 |
| Presence of Objects | 13 |
| Exposure to Sunlight | 8 |
| Motion Blur | 4 |



Problem Solution

Traffic Signs Detection and Recognition System

Problem Solution – TSDR System

Traffic Sign Recognition System

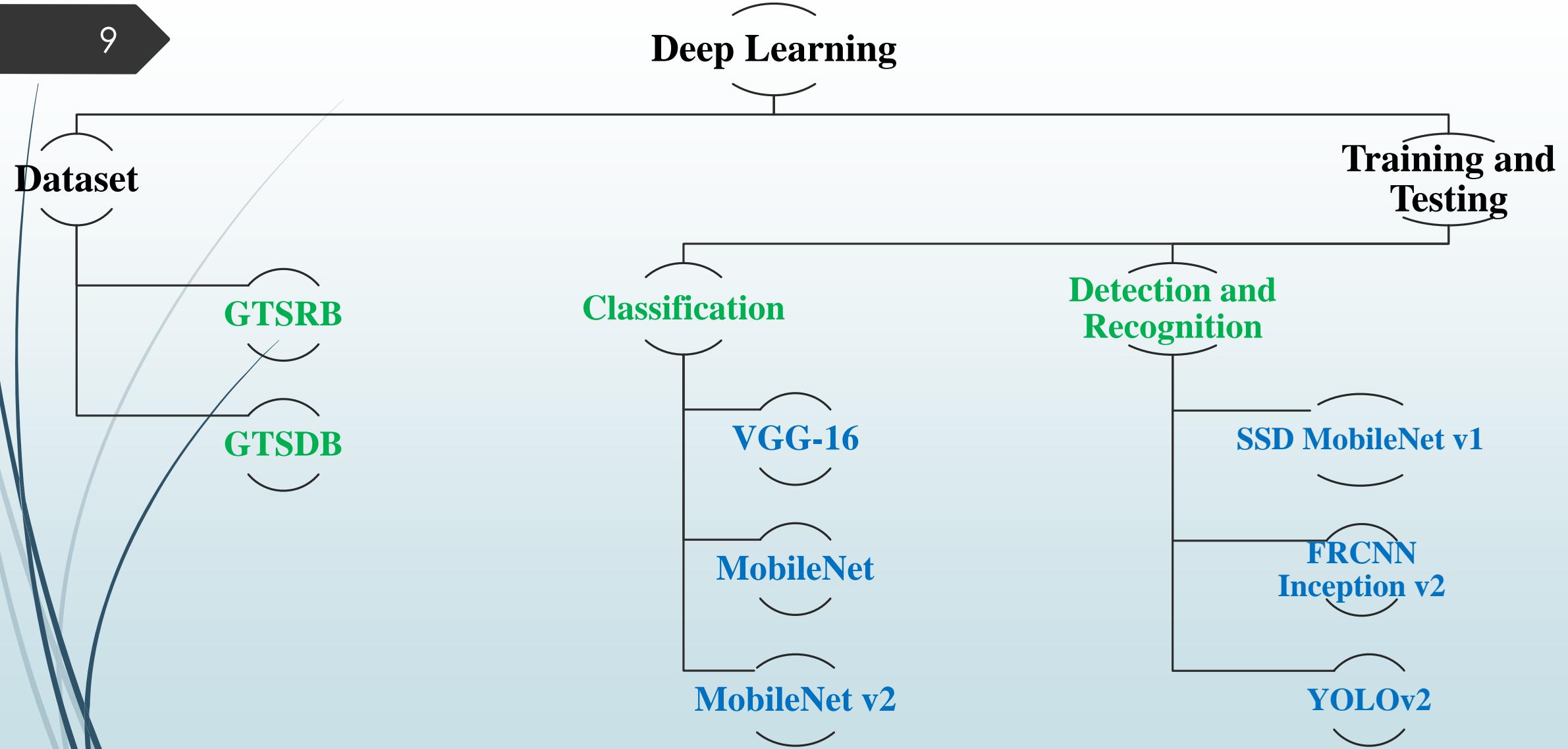
Advanced Driver Assistance System (ADAS) is a high-tech in-vehicle systems that are designed to increase road safety by alerting the driver of hazardous road conditions. Examples of the crucial ADAS sub-systems are Lane Departure, Collision Avoidance, and ***Traffic Signs Recognition (TSR)***.

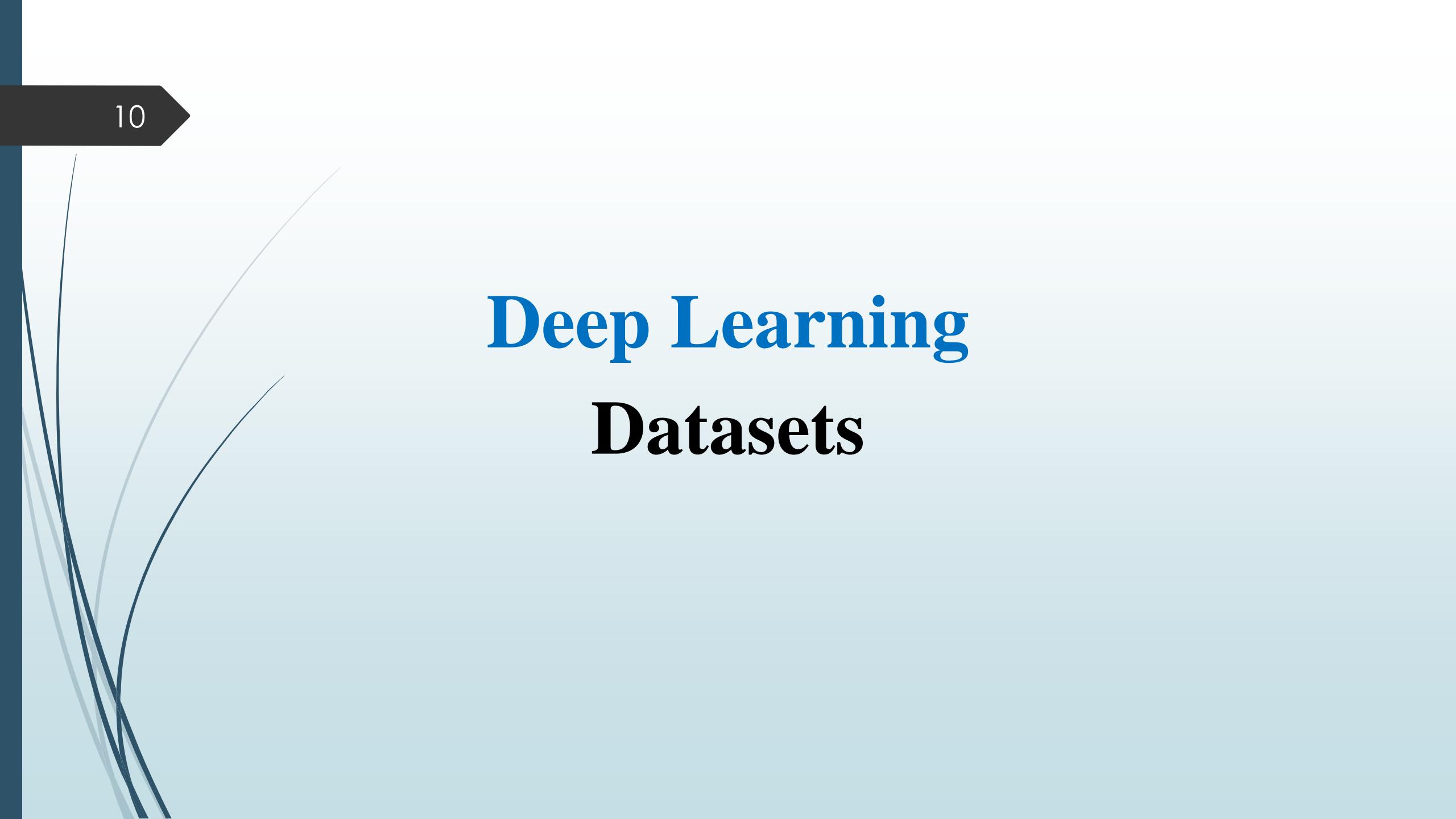


TSR system demos are being worked on now [3]



Our TSR system (v1) in action





Deep Learning Datasets

Deep Learning – Datasets

Datasets

GTSDB [4]

German Traffic Signs Detection Benchmark



GTSRB [5]

German Traffic Signs Recognition Benchmark



GTSRB dataset (52,000 images)

GTSDB dataset (900 images) Note the huge difference in the numbers because it will play a big role later on

Deep Learning

Deep learning – Transfer Learning

Transfer Learning

It is the improvement of learning in a new task through the transfer of knowledge from a related task that has already been learned.

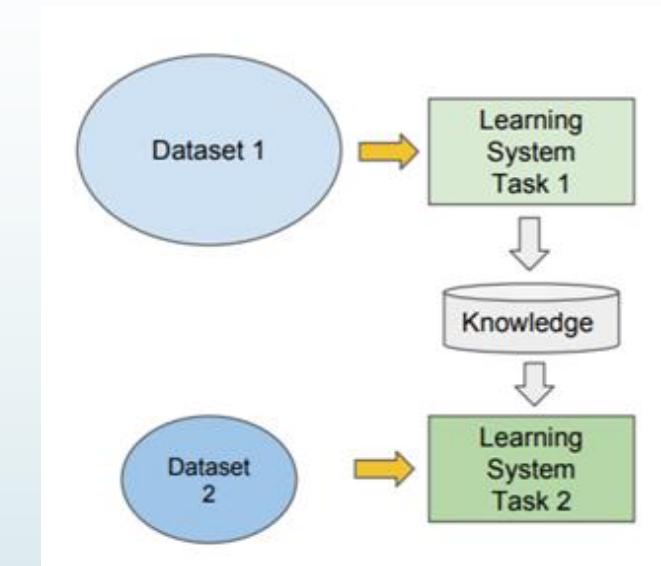
A. Classification

- VGG-16
- MobileNet v1
- MobileNet v2

B. Detection and Recognition

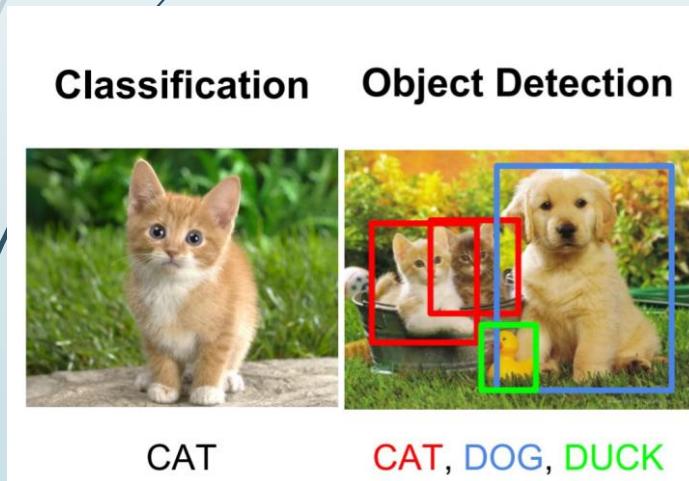
- SSD MobileNet v1
- Faster RCNN Inception v2
- Tiny-YOLOv2

We had talked about the classification portion in details during the first term exam, so we will go directly to the Detection and Recognition portion.



Real-time Detection

Real-time object detection is a much more difficult problem than image classification; the model has to first find the object (**detection**), trace it (**tracking**) and finally classify it (**recognition**).

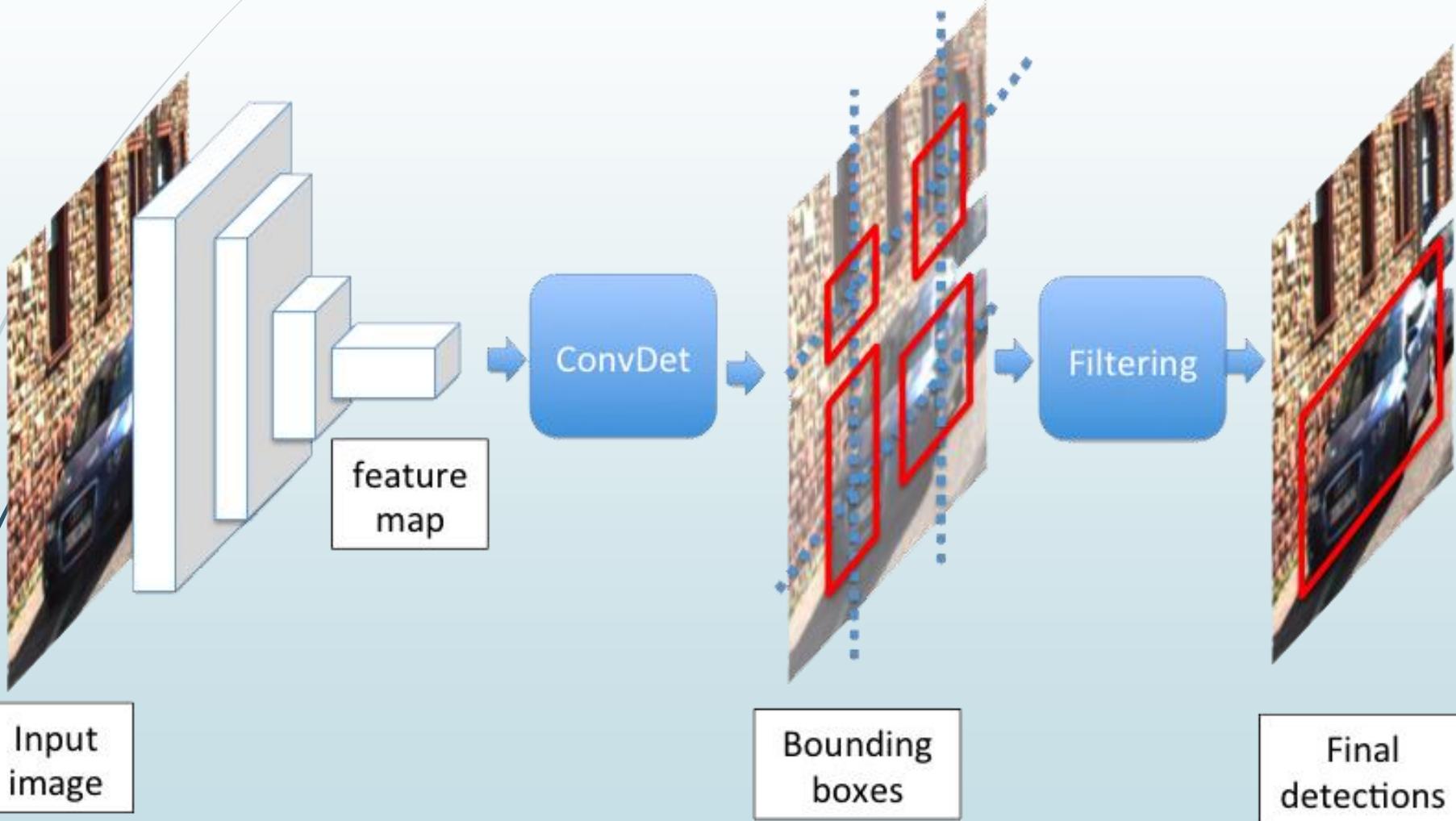


Classification vs Detection



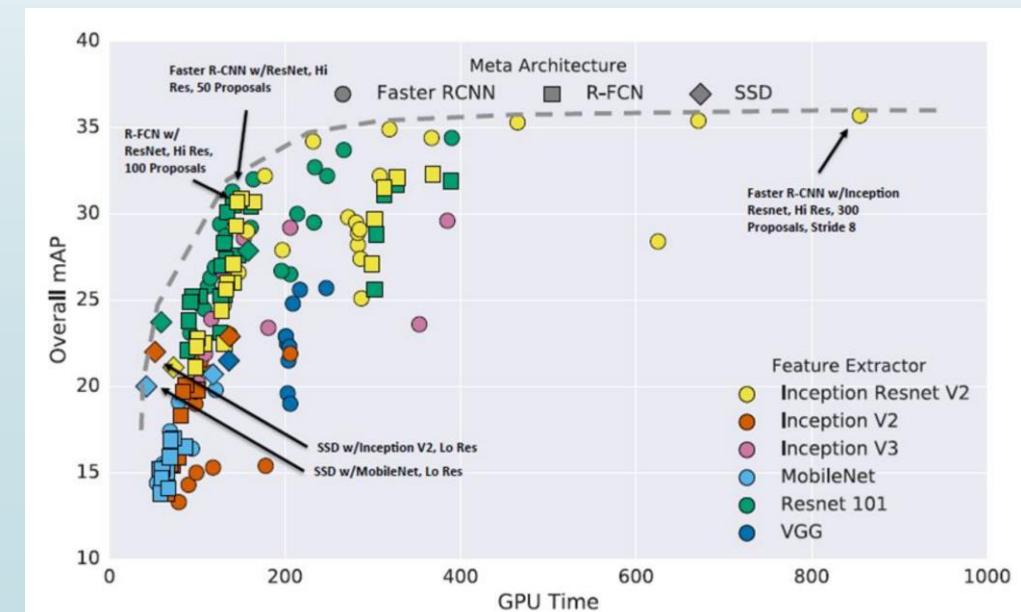
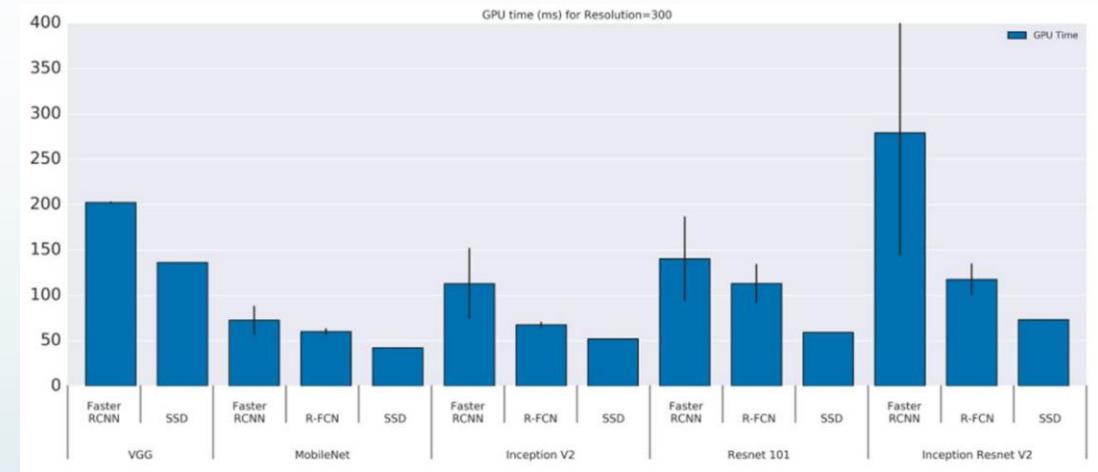
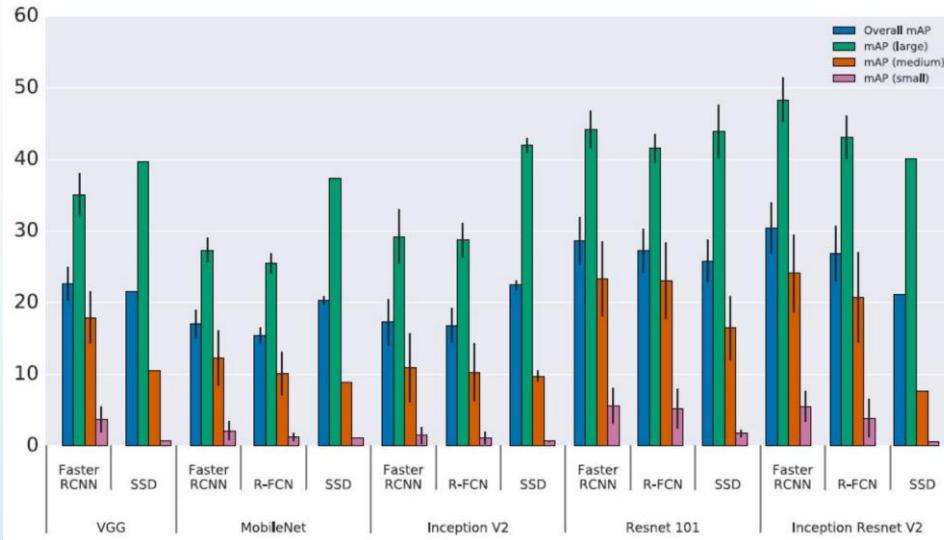
Real-time Traffic Signs Detection and Recognition

System Design



How an Object Detection model predicts the Region of Interests and classifies objects

Deep Learning – Models



| Parameters/model | SSD | F-RCNN |
|------------------|---------------|---------------|
| Accuracy | Less accurate | More accurate |
| Speed | Faster | Slower |



Deep Learning Detection and Recognition Training on SSD MobileNet Parameters

SSD MobileNet v1 Training

| | |
|-----------------------------------|---|
| Model | SSD MobileNet v1 |
| Number of epochs | 20k |
| Initial learning rate | 0.0002 |
| Learning rate decay | - |
| Data augmentation | Random grey scale Random 25% crop Random Vertical flip* |
| Number of classes | 43 |
| Number of training samples | 800 |
| Architecture Modification | Resizer = 300x300 Softmax classification (43) |
| Total loss | 1.5 |



Deep Learning Detection and Recognition Testing on SSD MobileNet Results

SSD MobileNet v1 Testing



```
I0329 16:36:32.211382 17120 tf_logging.py:115] PascalBoxes_PerformanceByCategory/AP@0.5IOU/b'snow': 0.422702
INFO:tensorflow:PascalBoxes_PerformanceByCategory/AP@0.5IOU/b'snow': 0.500000
INFO:tensorflow:PascalBoxes_PerformanceByCategory/AP@0.5IOU/b'speed limit 100': nan
INFO:tensorflow:PascalBoxes_PerformanceByCategory/AP@0.5IOU/b'speed limit 100': nan
INFO:tensorflow:PascalBoxes_PerformanceByCategory/AP@0.5IOU/b'speed limit 120': nan
INFO:tensorflow:PascalBoxes_PerformanceByCategory/AP@0.5IOU/b'speed limit 120': nan
INFO:tensorflow:PascalBoxes_PerformanceByCategory/AP@0.5IOU/b'speed limit 20': 0.142857
INFO:tensorflow:PascalBoxes_PerformanceByCategory/AP@0.5IOU/b'speed limit 30': 0.411128
INFO:tensorflow:PascalBoxes_PerformanceByCategory/AP@0.5IOU/b'speed limit 50': 0.369462
INFO:tensorflow:PascalBoxes_PerformanceByCategory/AP@0.5IOU/b'speed limit 60': nan
INFO:tensorflow:PascalBoxes_PerformanceByCategory/AP@0.5IOU/b'speed limit 60': nan
INFO:tensorflow:PascalBoxes_PerformanceByCategory/AP@0.5IOU/b'speed limit 70': 0.322278
INFO:tensorflow:PascalBoxes_PerformanceByCategory/AP@0.5IOU/b'speed limit 80': 0.071429
INFO:tensorflow:PascalBoxes_PerformanceByCategory/AP@0.5IOU/b'stop': 1.000000
INFO:tensorflow:PascalBoxes_PerformanceByCategory/AP@0.5IOU/b'stop': 0.111111
INFO:tensorflow:PascalBoxes_PerformanceByCategory/AP@0.5IOU/b'uneven road': nan
INFO:tensorflow:PascalBoxes_Precision/mAP@0.5IOU: 0.347989
INFO:tensorflow:Metrics written to tf summary.
I0329 16:36:32.419960 17120 tf_logging.py:115] PascalBoxes_PerformanceByCategory/AP@0.5IOU/b'traffic signal': 0.111111
```

Accuracy: 45%



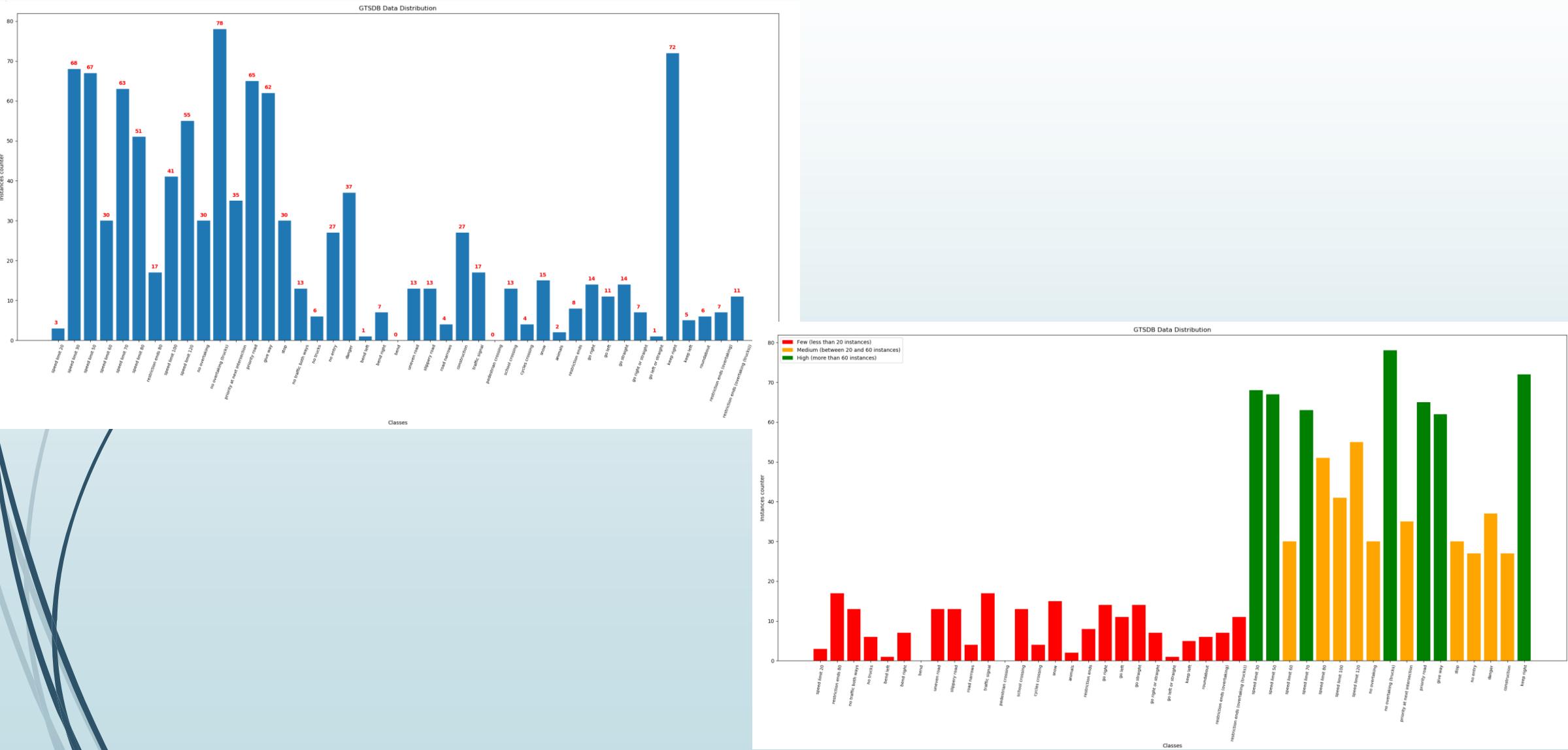
Exploratory Data Analysis

SSD MobileNet v1 Testing

What caused such low accuracy?

Let's analyze and visualize the dataset and see what went wrong...

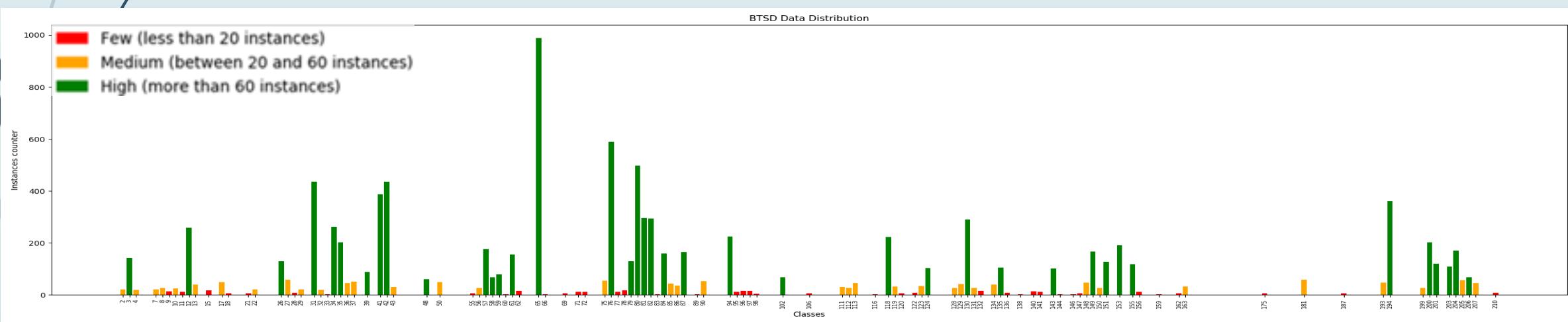
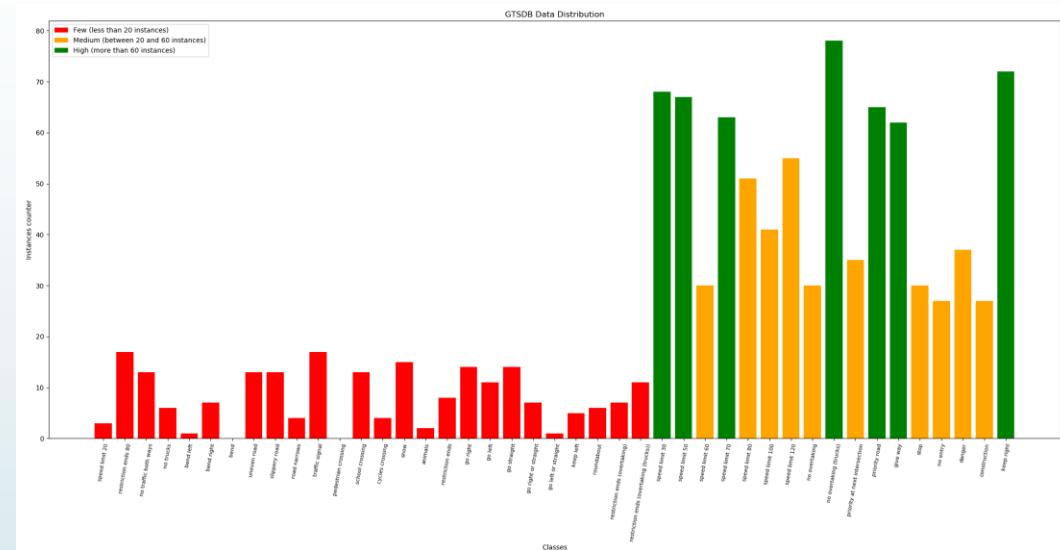
Data Visualization for GTSDB



Data Analysis – GTSDB vs BTSD

Notice the enormous difference between the green bars (number of classes that have more than 60 instances) in the GTSDB against that of the Belgium Traffic Signs Dataset (BTSD) [6].

Although the BTSD is found to be much better for our task, we unfortunately could not use it because it's **50GB**!



Solutions

Two possible solutions:

- Use F-RCNN instead of SSD since it is more accurate when it comes to small objects*

| Parameters/model | SSD | F-RCNN |
|------------------|---------------|----------------------|
| Accuracy | Less accurate | More accurate |
| Speed | Faster | Slower |

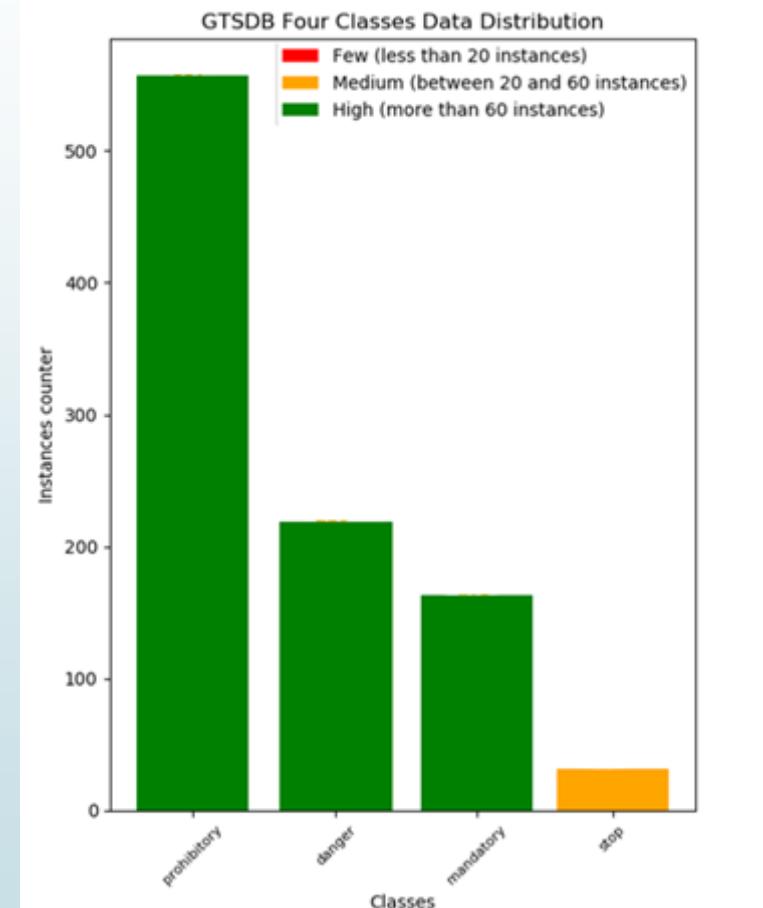
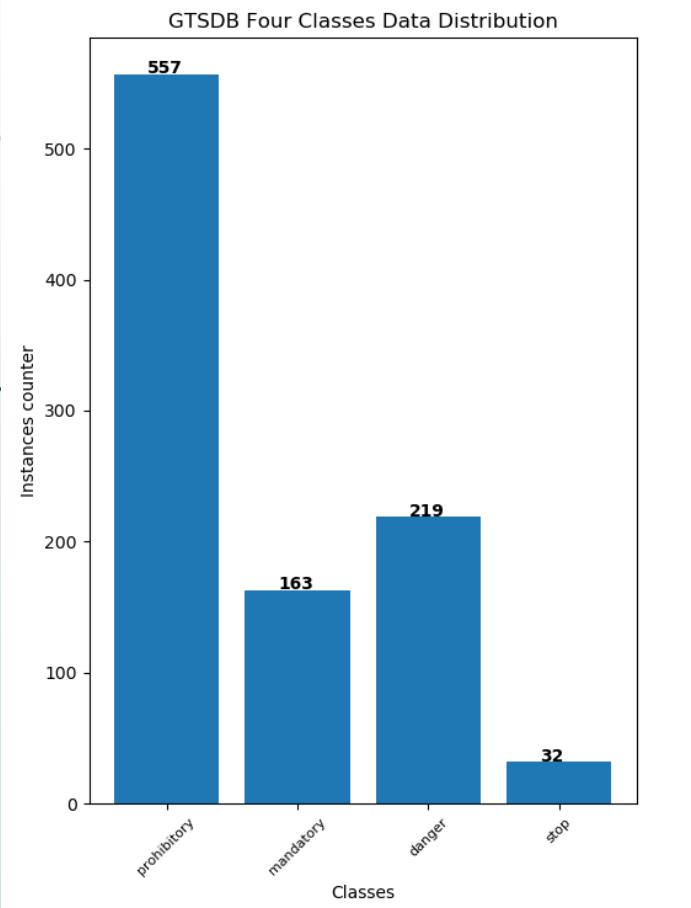
- Instead of training 800 images on 43 classes, we'd train 900 images on the three super classes and the Stop class

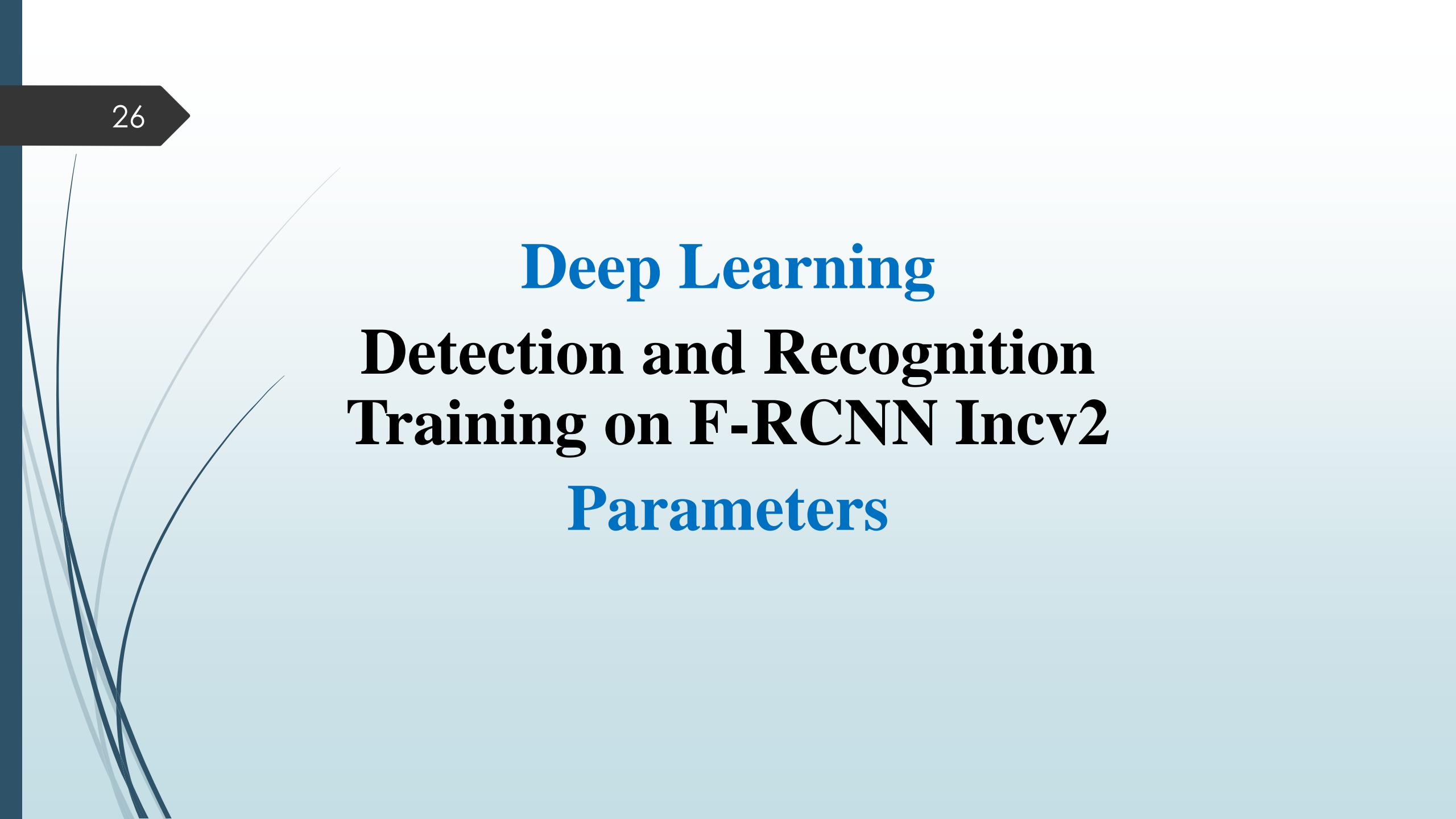
- **Prohibitory**
- **Mandatory**
- **Danger**
- **Stop**

| Category | Shape | Color | Example |
|--------------------|---------------------------|-----------------------------------|---|
| Prohibitory | Circular | Red, Blue, White & Black |  |
| Mandatory | Rectangular & Circular | Blue, White & Black |  |
| Danger | Triangular | Red, White & Black |  |

*<https://towardsdatascience.com/understanding-ssd-multibox-real-time-object-detection-in-deep-learning-495ef744fab>

Data Analysis for 4 Super-classes of GTSDB





Deep Learning

Detection and Recognition

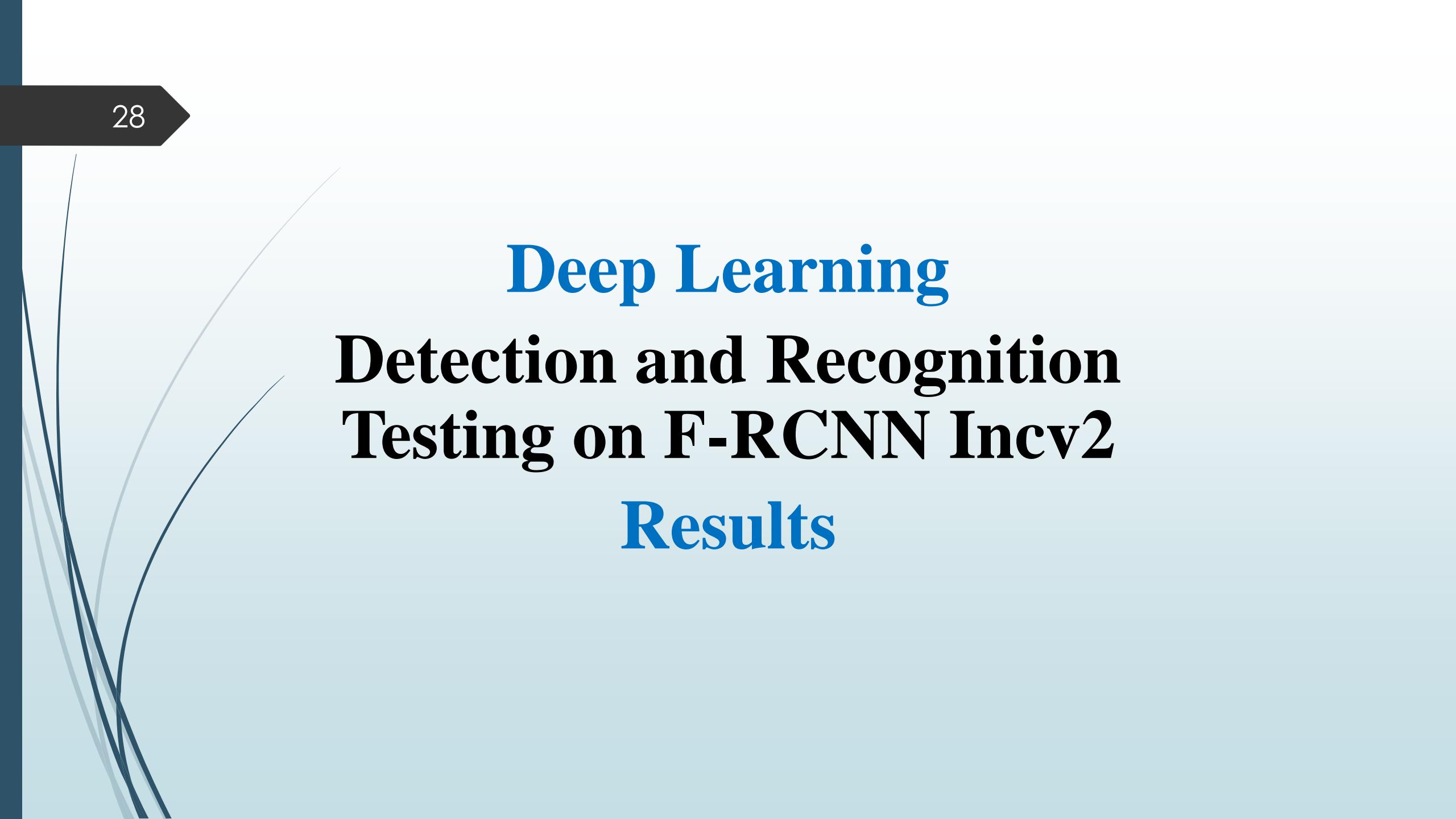
Training on F-RCNN Incv2

Parameters

FRCNN Inception v2 Training Parameters

| Model | SSD MobileNet v1 | F-RCNN Inception v2 |
|----------------------------|---|---|
| Number of epochs | 20k | 8.5k |
| Initial learning rate | 0.0002 | 0.0002 |
| Learning rate decay | - | 1e-3 every 3000 steps |
| Data augmentation | Random grey scale Random 25% crop Random Vertical flip* | Random grey scale Random 25% crop Random vertical flip Random horizontal flip |
| Number of classes | 43 | 4 |
| Number of training samples | 800 | 900 |
| Architecture Modification | Resizer = 300x300 Softmax classification (43) | Resizer: fixed aspect ratio IoU threshold: 0.7 NMS: 0.7 L2 Regularization Batch Normalization Drop out (30%) Softmax classification (4) |
| Total loss | 1.5 | 0.4 |

Comparison between the 1st aforementioned model (SSD MobileNet v1) and the 2nd used model (FRCNN Inception v2)



Deep Learning

Detection and Recognition Testing on F-RCNN Incv2

Results

Detection Testing (GTSDB) F-RCNN Inception v2



Accuracy: **95%**

Average speed on 720p video: **25FPS**
Average time on a 1080p image = **0.32sec**





Testing the FRCNN Inceptionv2 model

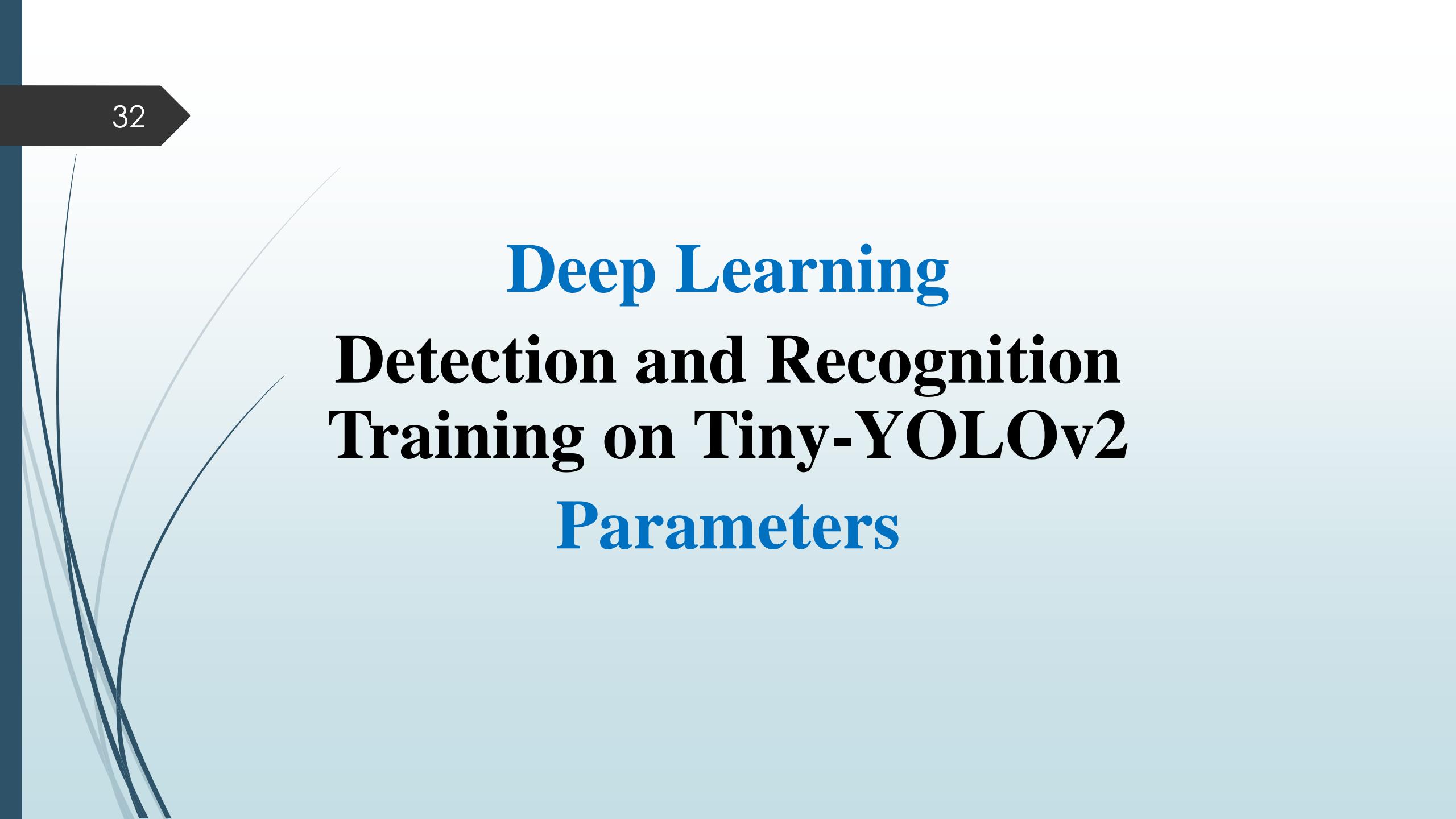
GTSDB Competition [7]

Our model scored an accuracy higher than most of the algorithms in the GTSDB competition and would have placed in the top 25 spot.*

<http://benchmark.ini.rub.de/?section=gtsdb&subsection=results>

| TEAM | METHOD | AREA UNDER CURVE | AVERAGE OVERLAP |
|----------------------------|---|------------------|-----------------|
| wgy@HIT501 | ELL_SVM2 (Prohibitive) | 100 % | 90.08 % |
| visics | boosted_intChn_ratio_scales (Prohibitive) | 100 % | 88.22 % |
| LITS1 | intColorShapeAppearance (Prohibitive) | 100 % | 86.91 % |
| glc12125 | robok (Prohibitive) | 100 % | 85.57 % |
| DSL_clusters | ToneMap+AfChunks (Prohibitive) | 100 % | 83.56 % |
| qichang.hu@adelaide.edu.au | sp_Cov_P (Prohibitive) | 100 % | 82.03 % |
| huqc@msn.com | spCov+chns_P (Prohibitive) | 99.99 % | 82.62 % |
| shawn_pan | intChn_50scales (Prohibitive) | 99.98 % | 88.99 % |
| BolognaCVLab | MSER-1+HOG-2+SVM+Heights+TL (Prohibitive) | 99.98 % | 84.95 % |
| BolognaCVLab | MSER-1+HOG+SVM+Heights+TL (Prohibitive) | 99.97 % | 84.37 % |
| qcom | VSSD3 (Prohibitive) | 99.89 % | 91.93 % |
| wgy@HIT501 | HOG_LDA_SVM (Prohibitive) | 99.78 % | 80.81 % |
| visics | boosted_intChn_7ops (Prohibitive) | 99.12 % | 88.88 % |
| huqc@msn.com | First try (Prohibitive) | 99 % | 82.54 % |
| s_trafficsign | DL2 (prohibitory) (Prohibitive) | 99 % | 86.34 % |
| wgy@HIT501 | ELL_SVM (Prohibitive) | 98.99 % | 90.17 % |
| hb@hit501 | hb_pro_0.8_0.6_13 (Prohibitive) | 98.98 % | 79.6 % |
| LITS1 | hog+svm1 (Prohibitive) | 98.97 % | 88.49 % |
| VJ+Filter | VJ+LBP+HSV+colorSIFT (Prohibitive) | 98.96 % | 86.33 % |
| exp | Multi-features filter (Prohibitive) | 98.96 % | 86.33 % |
| exp | exp-multi-pr (Prohibitive) | 98.91 % | 86.59 % |
| VJ+Filter | VJ+LBP+HSV (Prohibitive) | 98.87 % | 86.34 % |
| NII-UIT | light-colorSIFT_V2 (Prohibitive) | 98.11 % | 81.71 % |
| genius07 | vgg_detection (Prohibitive) | 98 % | 90.55 % |
| VJ+Filter | VJ+LBP+HSV+SIFT (Prohibitive) | 97.96 % | 86.33 % |
| VJ+Filter | test (Prohibitive) | 97.94 % | 86.58 % |
| LITS1 | hog+svm (Prohibitive) | 97.73 % | 87.8 % |
| huqc@msn.com | Second try (Prohibitive) | 97.02 % | 83.02 % |
| temp | frr (Prohibitive) | 97 % | 91.79 % |
| s_trafficsign | DL (prohibitory) (Prohibitive) | 97 % | 86.33 % |
| BolognaCVLab | MSER+HOG+SVM+Heights+TL (Prohibitive) | 96.01 % | 80.45 % |
| bkmw | haar_upscale (Prohibitive) | 95.82 % | 84.48 % |
| exp | Bag of visual word (Prohibitive) | 95.23 % | 87.64 % |
| abolabol | abolabol3 (Prohibitive) | 95 % | 92.49 % |
| NII-UIT | denseSIFT (Prohibitive) | 94.65 % | 87.48 % |
| ducluu | lbp_filter_16_20_wsize (Prohibitive) | 93.12 % | 85.37 % |
| exp | Bag of visual words (Prohibitive) | 92.34 % | 87.55 % |
| ShapeSaliency | ShapeSaliency+Color (Prohibitive) | 92.16 % | 85.49 % |
| Test | 12_STAGES_UPSIZE (Prohibitive) | 91.82 % | 82.91 % |
| Test | test_all (Prohibitive) | 91.49 % | 82.94 % |
| code monkey | 11D3 prohibitory (Prohibitive) | 91.4 % | 88.1 % |
| Test | 12_STAGES_UPSIZE (Prohibitive) | 91.15 % | 82.87 % |
| hoqmawla | hoqmawla3 (Prohibitive) | 91.14 % | 83.73 % |
| INI-RTCV | Viola-Jones (Prohibitive) | 90.81 % | 87.85 % |
| code monkey | Modified SSD (Prohibitive) | 88.8 % | 90.27 % |
| mraouf.cairo.4 | Prohibitory_13_21_(Prohibitive) | 88.6 % | 93.28 % |
| shawn_pan | intChn_MultiScale (Prohibitive) | 88.35 % | 87.94 % |
| huqc@msn.com | Combine1 (Prohibitive) | 88.11 % | 83.66 % |
| mraouf.cairo.3 | Prohibitory_Testing_13_20 (Prohibitive) | 87.64 % | 93.16 % |

Our model achieved an accuracy of 95% placing it in the top-25 spots

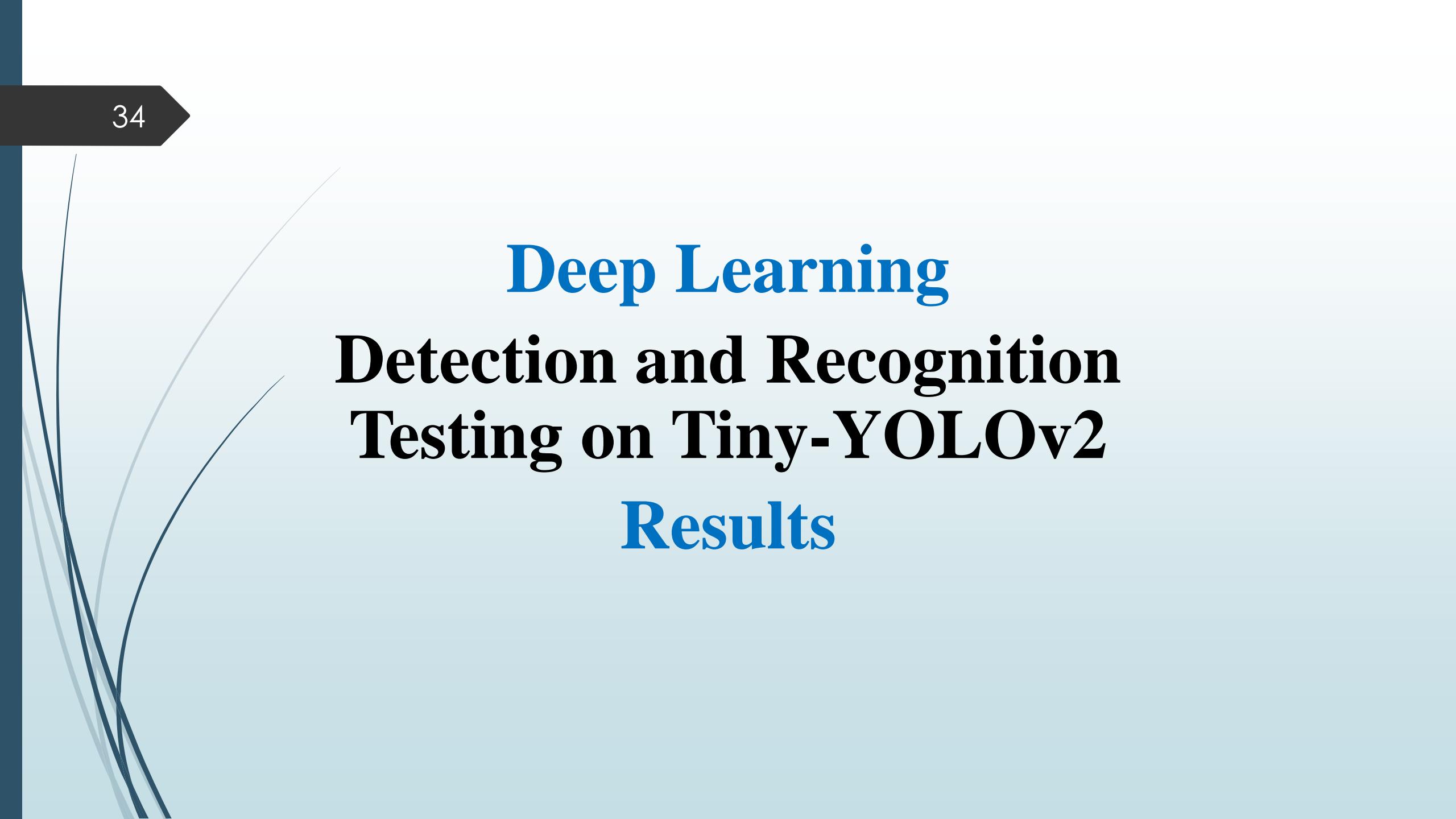


Deep Learning Detection and Recognition Training on Tiny-YOLOv2 Parameters

Tiny-YOLOv2 Training Parameters

| Model | SSD MobileNet v1 | F-RCNN Inception v2 | Tiny YOLOv2 |
|-----------------------------------|---|--|--|
| Number of epochs | 20k | 8.5k | 1.5k |
| Initial learning rate | 0.0002 | 0.0002 | 0.0002 |
| Learning rate decay | - | 1e-3 every 3000 steps | - |
| Data augmentation | Random grey scale Random 25% crop Random Vertical flip* | Random grey scale Random 25% crop Random Vertical flip Random horizontal flip | Random grey scale Random Vertical flip Random horizontal flip |
| Number of classes | 43 | 4 | 4 |
| Number of training samples | 800 | 900 | 900 |
| Total loss | 1.5 | 0.4 | 2.8 |

Comparison between the first two models (SSD MobileNetv1 and FRCNN Inception v2) and Tiny TOLOv2



Deep Learning Detection and Recognition Testing on Tiny-YOLOv2 Results

Detection Testing (GTSDB) – Tiny-YOLOv2



Accuracy: 73%

Average speed on 720p video: 70FPS
Average time on a 1080p image = 0.02sec





Testing the YOLOv2 model

Conclusion

| Model | SSD MobileNet v1 | F-RCNN Inception v2 | Tiny YOLOv2 |
|----------------------------|---|--|---|
| Number of epochs | 20k | 8.5k | 1.5k |
| Initial learning rate | 0.0002 | 0.0002 | 0.0002 |
| Learning rate decay | - | 1e-3 every 3000 steps | - |
| Data augmentation | Random grey scale Random 25% crop Random Vertical flip* | Random grey scale Random 25% crop Random Vertical flip Random horizontal flip | Random grey scale Random Vertical flip Random horizontal flip |
| Number of classes | 43 | 4 | 4 |
| Number of training samples | 800 | 900 | 900 |
| Total loss | 1.5 | 0.4 | 2.8 |
| Accuracy | 45% | 95% | 73% |
| Speed per image (sec) | 0.15 | 0.32 | 0.02 |
| Speed (FPS) | 32FPS | 25FPS | 70FPS |

Comparison between all the models' results obtained while testing on the host PC

Implementation

Raspberry Pi 3
Model B+

iMX6Q

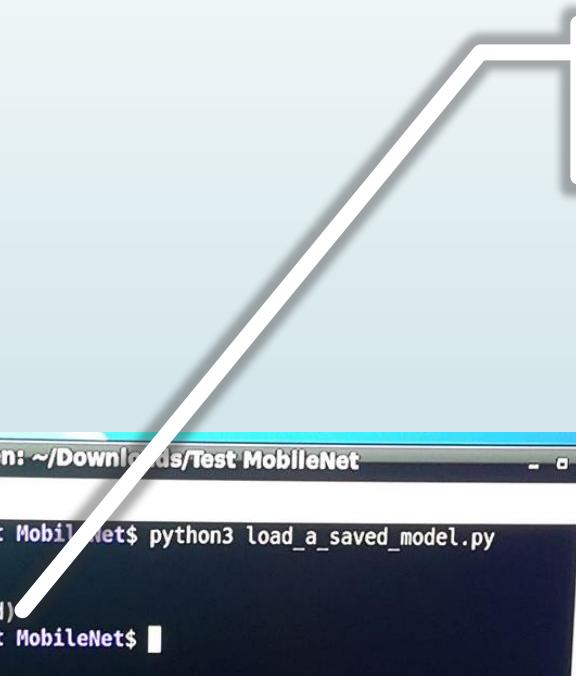
TASS PreScan



Embedded System Implementation iMX6Q

Testing on the iMX6Q

Tensorflow was too heavy for the board's CPU that it crashed every time we tried to create a variable and initiate a session.



```
ubuntu@nitrogen: ~/Downloads/Test MobileNet
File Edit Tabs Help
ubuntu@nitrogen:~/Downloads/Test MobileNet$ python3 load_a_saved_model.py
[INFO] Import done
[INFO] Loading model...
Illegal instruction (core dumped)
ubuntu@nitrogen:~/Downloads/Test MobileNet$
```

Error message whenever we tried loading a Tensorflow model despite how light it is

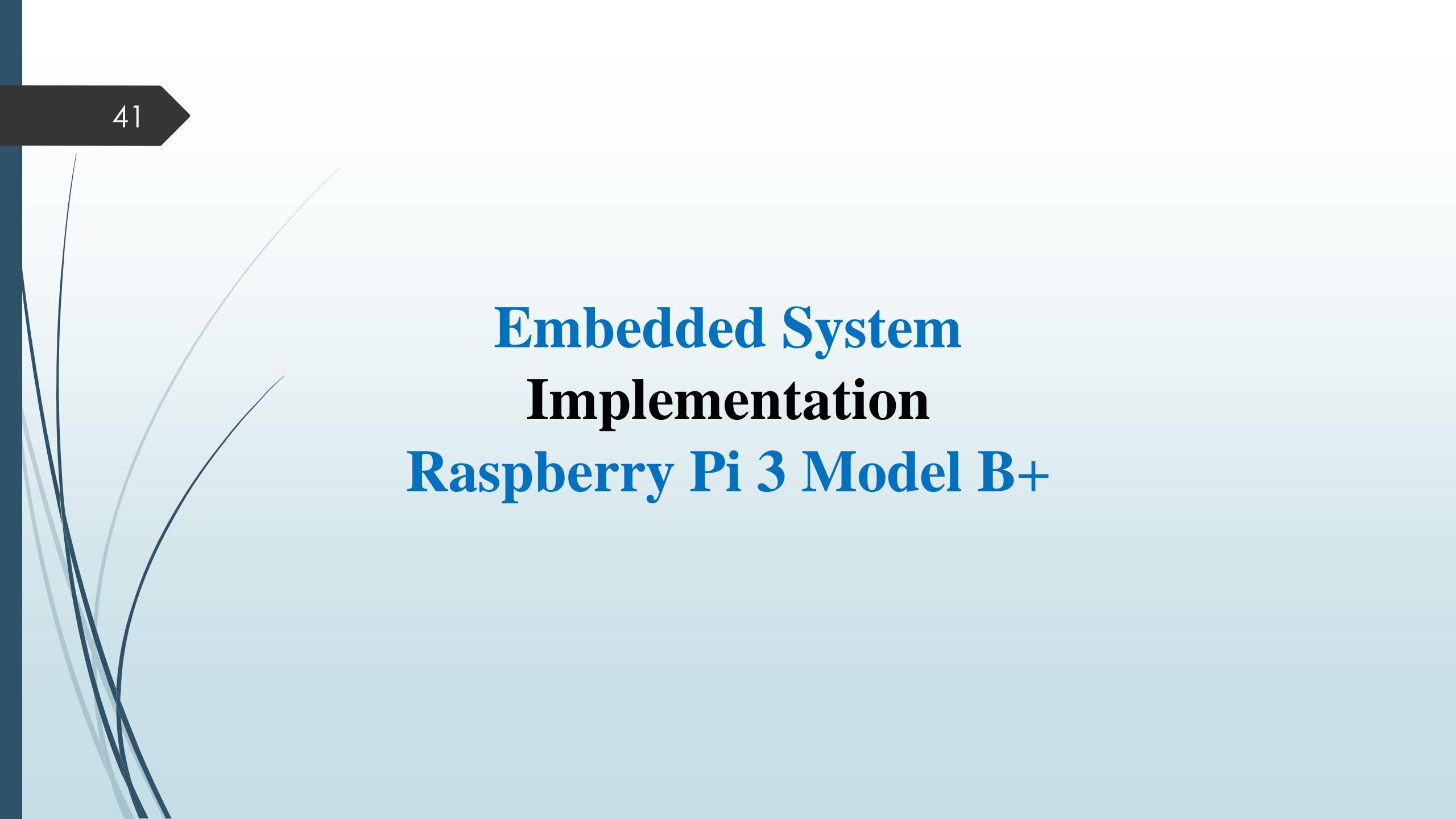


| iMX6Q | |
|-------|------------------------------------|
| CPU | ARM Cortex-A9 (Quad-Core) 1 GHZ |
| RAM | 1GB DDR3 |
| GPU | Vivante GC2000 |

iMX6Q specs



iMX6Q



Embedded System Implementation Raspberry Pi 3 Model B+

Raspberry Pi 3 Model B+ vs Host PC

| | iMX6Q | RPi 3B+ | Host PC |
|-----|------------------------------------|--------------------------------------|---------------------------|
| CPU | ARM Cortex-A9 (Quad-Core) 1 GHZ | ARM Cortex-A53 (Quad-Core) 1.2GHz | I7 6700k Quad-core 3.2GHz |
| RAM | 1GB DDR3 | 1GB LP DDR2 | 16GB DDR3 |
| GPU | Vivante GC2000 | Dual Core Video Core IV | Nvidia GTX 1070 6GB |

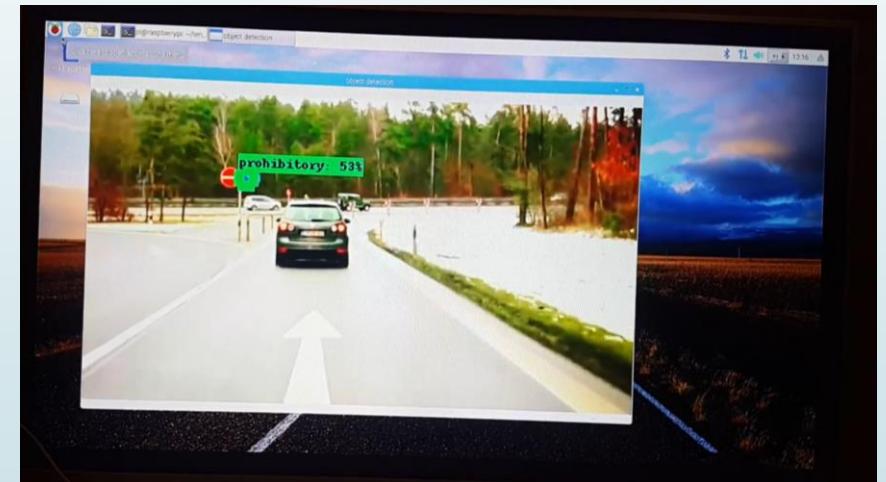
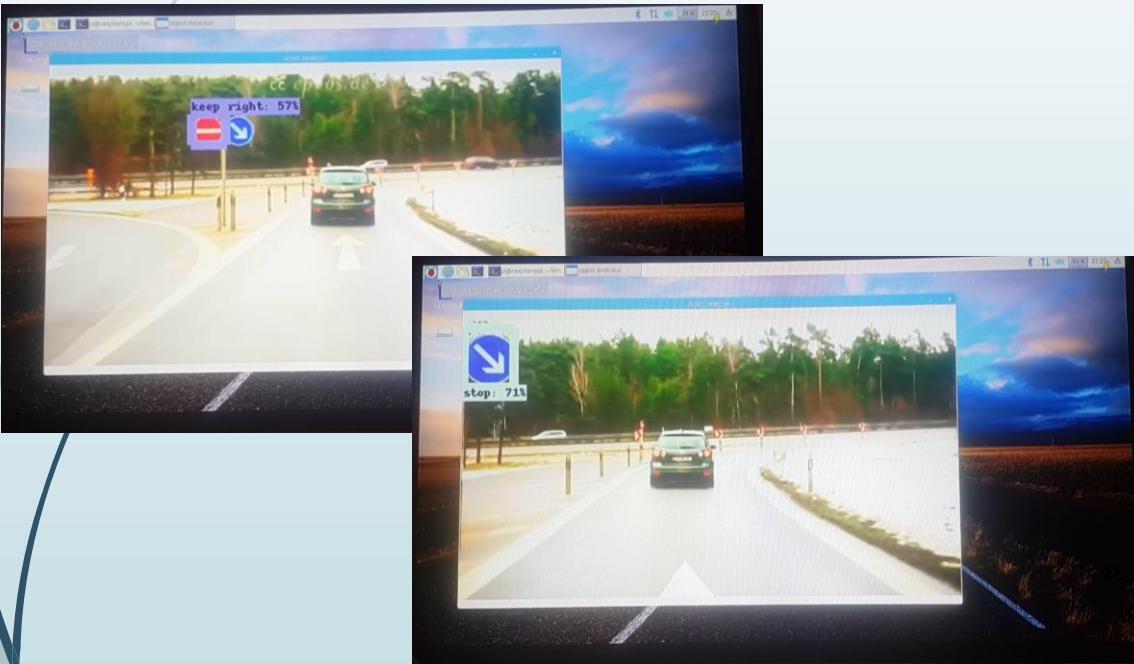
iMX6Q vs. RPi 3 Model B+ vs. Host PC specs

Testing the TSDR System on RPi 3 Model B+

Models used: SSD MobileNetv2 (43 classes and 4 classes)

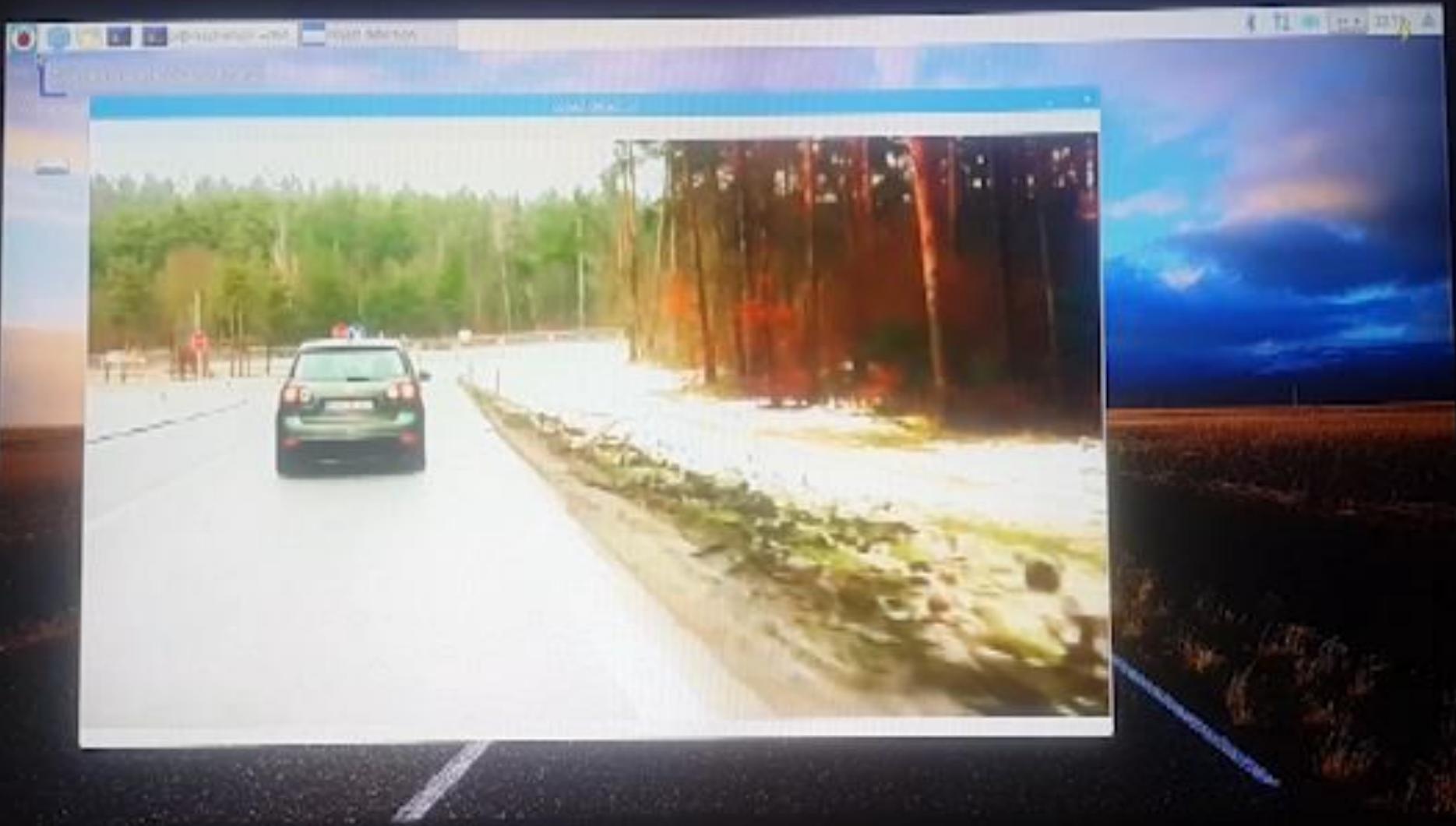
Video resolution: 640x480 (480p)

Average speed (FPS): 1FPS

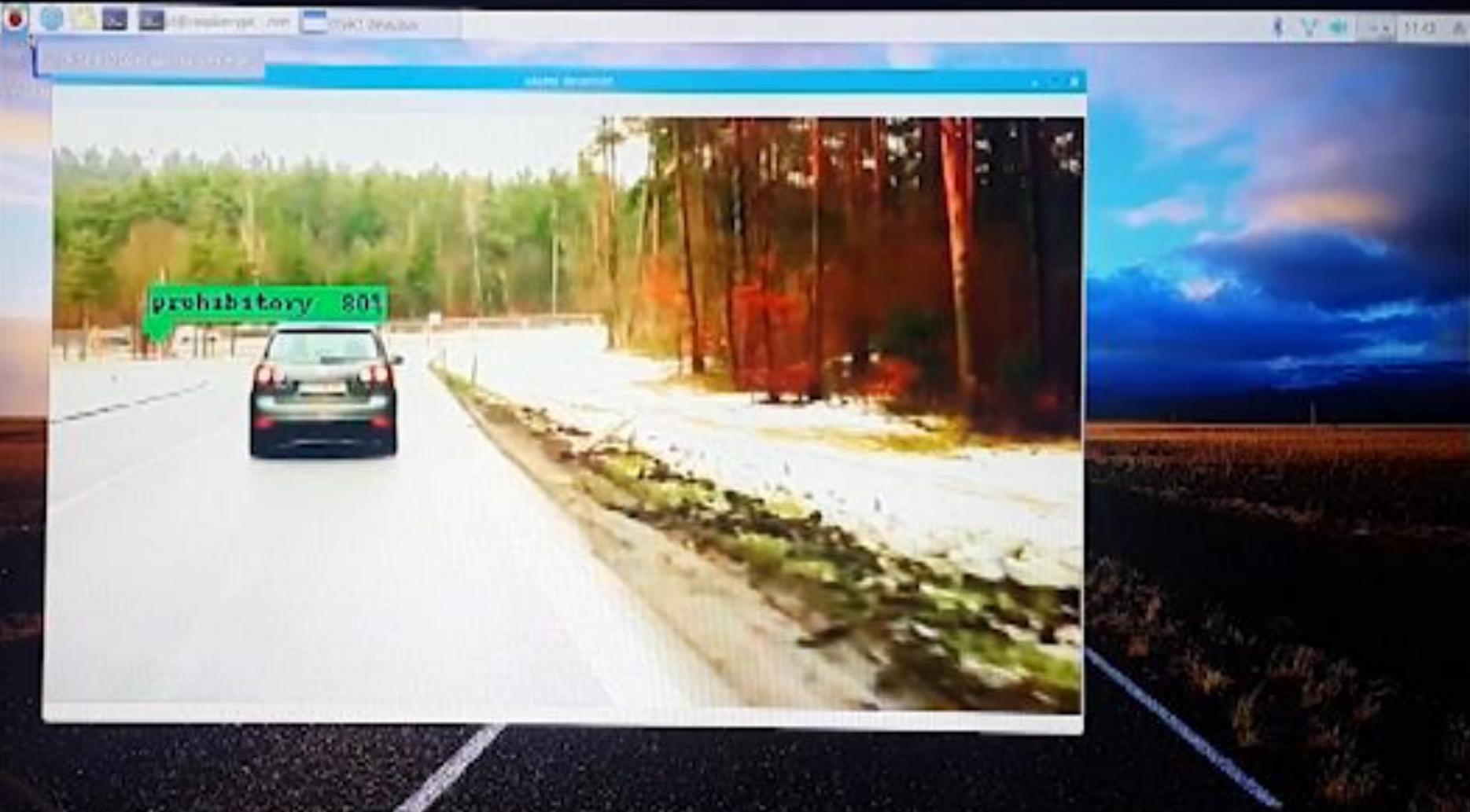


Testing the SSD MobileNet v2 model – trained on 4 classes – on RPi 3B+

Testing the SSD MobileNet v2 model – trained on 43 classes – on RPi 3B+



Testing the SSD MobileNet v2 model – trained on 43 classes – on RPi 3B+



Testing the SSD MobileNet v2 model – trained on 4 classes – on RPi 3B+



Virtual Board Implementation TASS PreScan

TASS PreScan Implementation

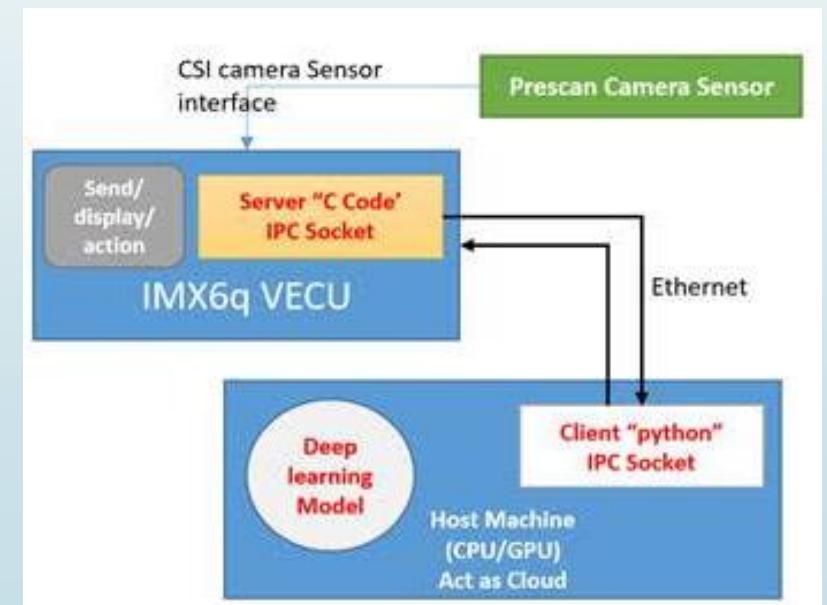
Introduction

TASS PreScan [8] is a virtual simulation for a self-driving car recently acquired by *Siemens* in **2018** with the purpose to simulate real-life scenarios that might face a self-driving car.

We've had the pleasure to implement our TSDR System in PreScan.

Process

- A *real-time video* is generated by *PreScan*.
- Each *frame* is *flattened* to 1-D.
- The *1-D frame* is *sent* to our Host PC.
- *Our algorithm* converts the received bytes *1-D frame* into a *2D RGB frame*.
- The *2D frame* is then passed to the F-RCNN Inception v2 model.
- The resulting *detected frame* is *shown* and *saved* in the Host PC.

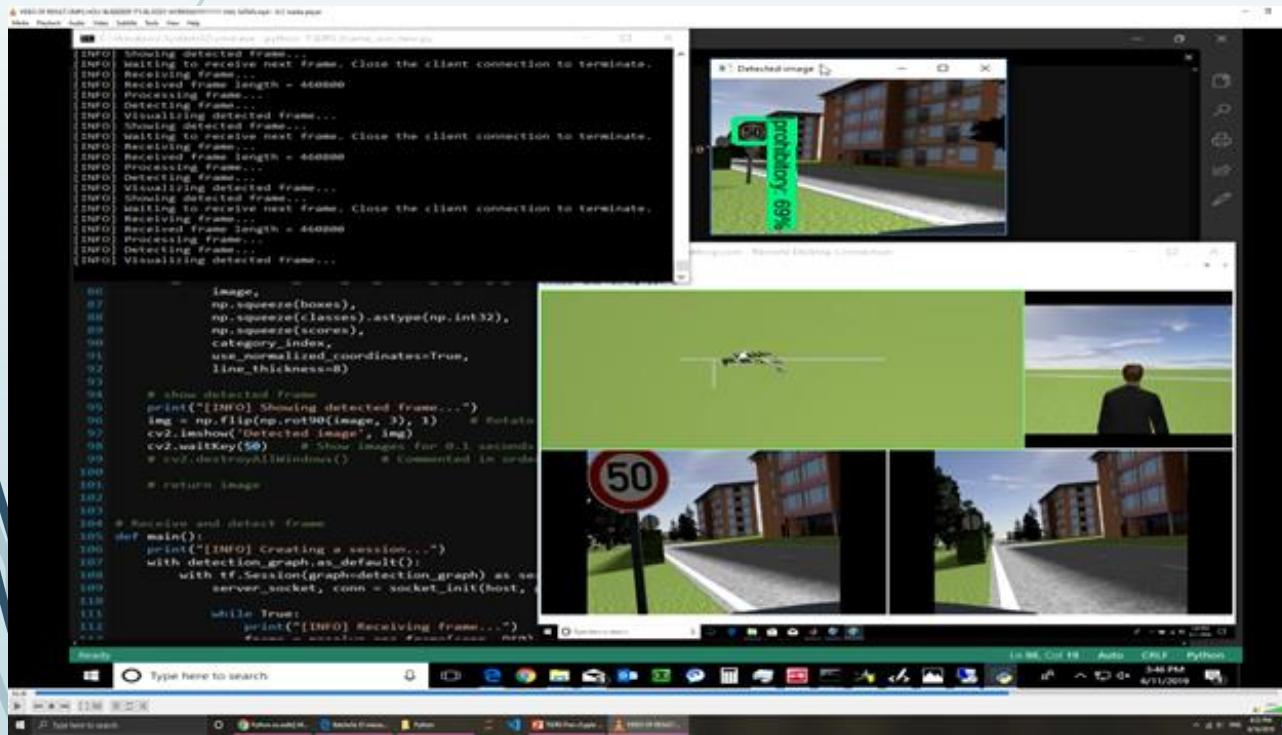


Process of detecting frames from PreScan

PreScan Implementation - Results

Model: FRCNN Inception v2

FPS: PreScan speed – 4



FRCNN Detecting PreScan signs

C:\Windows\System32\cmd.exe

```
[INFO] Showing detected frame...
[INFO] Waiting to receive next frame. Close the client connection to terminate.
[INFO] Receiving frame...
[INFO] Received frame length = 460800
[INFO] Processing frame...
[INFO] Detecting frame...
[INFO] Visualizing detected frame...
[INFO] Showing detected frame...
[INFO] Waiting to receive next frame. Close the client connection to terminate.
[INFO] Receiving frame...
[INFO] Received frame length = 460800
[INFO] Processing frame...
[INFO] Detecting frame...
[INFO] Visualizing detected frame...
[INFO] Showing detected frame...
[INFO] Waiting to receive next frame. Close the client connection to terminate.
[INFO] Receiving frame...
[INFO] Client disconnected!
[INFO] Connection closed!
```

C:\Users\markma\Desktop\New folder\research\object_detection>python TSDRS_Frame_with_new.py

```
86     image,
87     np.squeeze(boxes),
88     np.squeeze(classes).astype(np.int32),
89     np.squeeze(scores),
90     category_index,
91     use_normalized_coordinates=True,
92     line_thickness=8)

93
94     # show detected frame
95     print("[INFO] Showing detected frame...")
96     img = np.flip(np.rot90(image, 3), 1)      # Rotate
97     cv2.imshow('Detected image', img)
98     cv2.waitKey(50)    # Show images for 0.1 seconds
99     # cv2.destroyAllWindows()      # Commented in order
100
101    # return image
102
103
104 # Receive and detect frame
105 def main():
106     print("[INFO] Creating a session...")
107     with detection_graph.as_default():
108         with tf.Session(graph=detection_graph) as sess:
109             server_socket, conn = socket_init(host, port)
110
111             while True:
112                 print("[INFO] Receiving frame...")
113                 frame = receive_one_frame(conn, 0.02)
```

intorg.com - Remote Desktop Connection

The image shows a Windows desktop environment. On the left, a terminal window titled 'C:\Windows\System32\cmd.exe' displays log messages from a Python script named 'TSDRS_Frame_with_new.py'. The script performs object detection on video frames, printing INFO-level messages about receiving and processing frames. On the right, a screenshot of a video frame is shown with three bounding boxes and labels: 'prescan' (top), 'Human' (middle), and 'Car' (bottom). A status bar at the bottom of the desktop window indicates 'Ready'.

Models Implementation Conclusion

| Parameters | Results | | |
|---------------------------|----------------------|------------------------|-------------|
| Model | SSD MobileNet v2 (4) | F-RCNN Inception v2 | Tiny YOLOv2 |
| Accuracy | 75% | 95% | 73% |
| Speed per image (Host PC) | 0.21 | 0.32 | 0.02 |
| FPS (Host PC) | 30 | 25FPS | 70FPS |
| Speed TASS PreScan | Not tested | TASS' speed – 4 frames | Not tested |
| Speed RPi 3B+ | 1FPS | Could not be loaded | Not tested |

Implementation results: SSD MobileNet v2 vs. F-RCNN Inception v2 vs YOLO v2

Our Results vs Previous TSDR Systems

| Parameters | Our Results | | Previous Systems | |
|---------------------------|----------------------|------------------------|------------------|-------------------|
| Algorithm | SSD MobileNet v2 (4) | F-RCNN Inception v2 | HoG + SVM [9] | MSER + CNN [10] |
| Dataset | GTSDB | GTSDB | GTSDB | GTSDB |
| Accuracy | 75% | 95% | 88.9% | 95% |
| Speed per image (Host PC) | 200ms | 324ms | - | 450ms (1280x1024) |
| FPS (Host PC) | 30 | 25FPS | 8-12FPS | - |
| Speed TASS PreScan | Not tested | TASS' speed – 4 frames | Not tested | Not tested |
| Speed RPi 3B+ | 1FPS | Could not be loaded | Not tested | Not tested |

Implementation results comparison – Our results vs previous results

References

[1] “ASIRT Road Accident,” [Online]

Available: <https://www.asirt.org/safe-travel/road-safety-facts/>

[2] “World Health Organization,” [Online]

Available: <https://www.who.int/news-room/fact-sheets/detail/the-top-10-causes-of-death>

[3] “Ford Traffic Signs Recognition,” [Online]

Available: <https://www.youtube.com/watch?v=BQgulv2hbuU>

[4] “GTSDB,” [Online]

Available: <http://benchmark.ini.rub.de/?section=gtsdb&subsection=news>

[5] “GTSRB,” [Online]

Available: <http://benchmark.ini.rub.de/?section=gtsrb&subsection=news>

[6] “Belgium Traffic Signs Dataset,” [Online]

Available: http://www.vision.ee.ethz.ch/~timofter/traffic_signs/

[7] “GTSDB Competition,” [Online]

Available: <http://benchmark.ini.rub.de/?section=gtsdb&subsection=results>

[8] “TASS PreScan,” [Online]

Available: <https://tass.plm.automation.siemens.com/prescan>

References

- [9] Chunsheng Liu, Faliang Chang, Zhenxue Chen, and Dongmei Liu, “Fast Traffic Sign Recognition via High-Contrast Region Extraction and Extended Sparse Representation,” **IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS**, VOL. 17, NO. 1, JANUARY 2016
- [10] LUO *et al.* “Traffic sign recognition using multi-task convolutional neural network,” **IEEE transactions on intelligent transportation systems**, vol. 19, no. 4, april 2018



Thank You!



Backup Slides

Classification

A. Classification

Image classification is the problem in which the model is given a small image of an object and it recognizes to which class (category) this object belongs.



Traffic sign classification



Deep Learning Classification Training Parameters

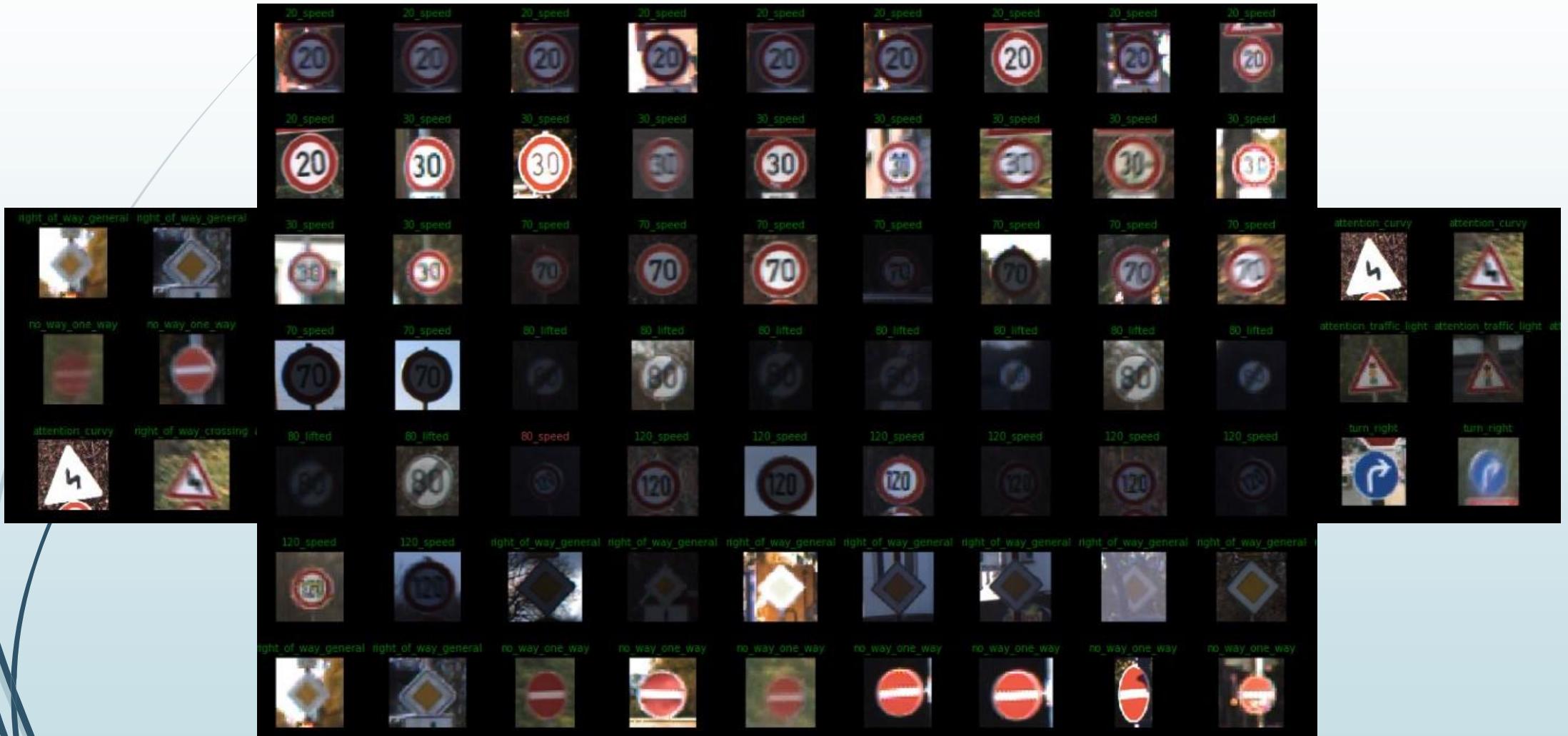
Training Parameters

| Model | MobileNet v1 | MobileNet v2 |
|------------------------------|---|---|
| Number of epochs | 10 | 10 |
| Initial learning rate | 0.0002 | 0.0002 |
| Data augmentation | <ul style="list-style-type: none"> • Random grey scale • Random 25% crop • Random vertical flip • Random 20-60% brightness shift • Random contrast shift | <ul style="list-style-type: none"> • Random grey scale • Random 25% crop • Random vertical flip • Random 20-60% brightness shift • Random contrast shift |
| Number of classes | 43 | 43 |
| Number of training samples | 39, 200 | 39, 200 |
| Number of validation samples | 12, 800 | 12, 800 |
| Total loss achieved | 0.54 | 0.04 |
| Training accuracy | 82% | 99.8% |



Deep Learning Classification Testing Results

Testing MobileNetv2



Green = Correct prediction

Some testing results

Red = Incorrect prediction

GTSRB Competition [5]

*Our model scored an accuracy higher than that of the winning algorithm in the GTSRB competition**

| TEAM | METHOD | TOTAL | SUBSET |
|-----------------------------|--|--------|--------|
| [156] DeepKnowledge Seville | CNN with 3 Spatial Transformers | 99.71% | 99.71% |
| [3] IDSIA ★ | Committee of CNNs | 99.46% | 99.46% |
| [155] COSFIRE | Color-blob-based COSFIRE filters for object recogn | 98.97% | 98.97% |
| [1] INI-RTCV ★ | Human Performance | 98.84% | 98.84% |
| [4] sermanet ★ | Multi-Scale CNNs | 98.31% | 98.31% |
| [2] CAOR ★ | Random Forests | 96.14% | 96.14% |
| [6] INI-RTCV | LDA on HOG 2 | 95.68% | 95.68% |
| [5] INI-RTCV | LDA on HOG 1 | 93.18% | 93.18% |
| [7] INI-RTCV | LDA on HOG 3 | 92.34% | 92.34% |

Accuracy = 99.832%

The winning algorithm scored 99.7% accuracy whilst our model achieved 99.8%

* <http://benchmark.ini.rub.de/?section=gtsrb&subsection=results>