GEO SMART ASIA 2018

Locate #Locate18

# Real-time image-based parking occupancy detection using deep learning

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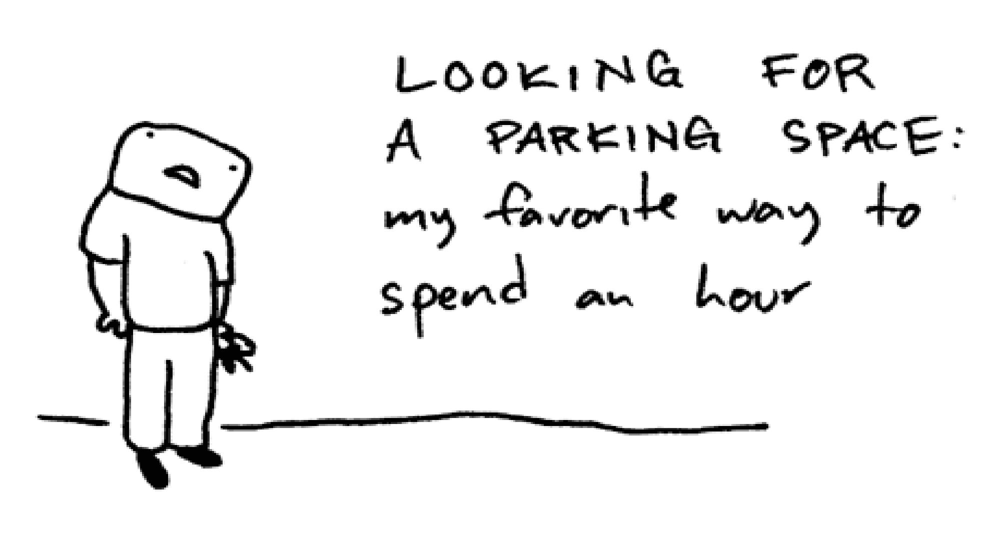
# Prologue

**Does that mean anything?**




**Stop ‘n’ go braking**

**The average driver spends 106+ days looking for a parking space**

# What can that result?



A fight over parking space has ended in tragedy, with a man losing his life after being kidnapped and brutally thrashed.

**MAN KIDNAPPED, BEATEN UP OVER PARKING SPAT**

**SPOT OF BOTHER:** The incident took place on Friday afternoon, when the victim objected to the driver, Thakur, parking his vehicle at this spot in Sion. PIC/DATTA KUMBHAR

When Subramaniam (50) asked the accused to park ahead, since the car was blocking the way, the driver and his friend assaulted the victim, bundled him into their car and drove him around for an hour before dumping him on the road. **Sagar Rajput** reports on P2

*mid-day's report on March 24*


# What can be done?

**The root cause**

**Searching for a parking spot, instead of moving towards one.**

**Solution**


**Real-time parking occupancy details.**
**Reliable guidance to vacant spots.**

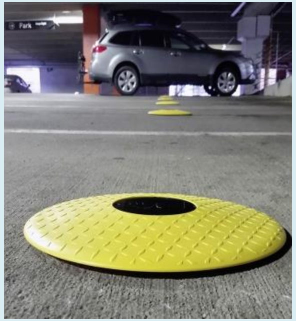
# Available options *(Ichihashi et al., 2009)*

### Counter-based systems

- Sensors at entry and exit
- Not for open spaces
- Does not provide location of vacant parking spot

### Camera-based systems

- Existing CCTV network
- Need direct visibility
- Less reliable compared to sensor-based systems



### Wired and wireless sensor-based systems

- Ultrasonic, infrared light or wireless magnetic-based
- High cost (~$40/ sensor) *(True, 2007)*
- 1 parking space = 1 sensor
- + processing units and transceivers for wireless sensors
- Highly reliable and accurate

# Our Solution: Camera-based systems

Intended applications

On-street parking and other open spaces

Motivations

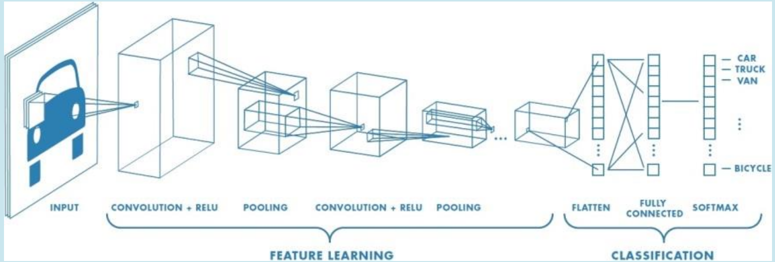

- No additional cost
- Can use existing CCTV networks


- learning ability getting closer to human cognition

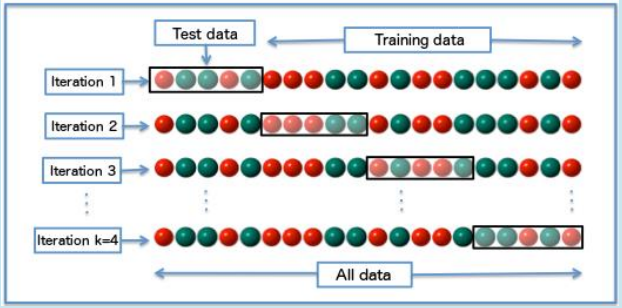
# Some unfamiliar terms

## Transfer learning

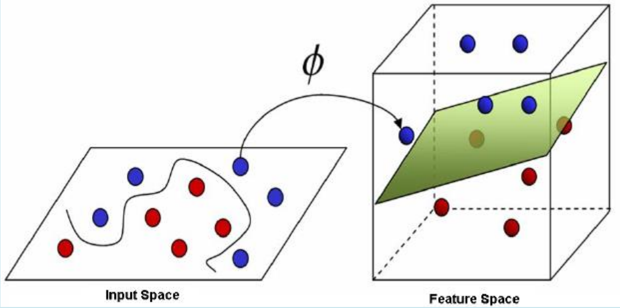
## Convolutional Neural Networks (CNNs)




## Cross validation




## Support Vector Machines (SVMs)



# Camera-based systems: The story so far

**Input images**

## Feature extraction

### Pre-defined (hand-crafted) features

- Edges, colour, texture, ……
- Low transfer learning ability (~89%)
- Susceptible to the variation in appearance

### Automatic feature detection

- Deep CNNs
- State-of-the-art performance for image classification
- High transfer learning ability (~95%)
- Robust to change in appearance

## Classification

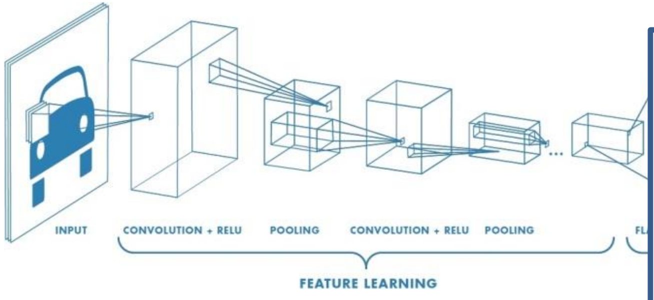
### Machine learning

SVMs, Neural Networks, Bayesian classifiers, ensembles of classifiers….

# Contribution to the story: Novelty

- *(Valipour et al., 2016; Amato et al., 2016; Amato et al., 2017)*
  - Fine-tune existing pre-trained CNNs
  - Accuracies up to 99.6 % for cross-validation process
  - Accuracies up to 95.6 % for transfer learning processes

- Current research
  - Use binary SVM classifier instead
  - Report better accuracies
  - A detailed analysis is performed to identify the parameters that affect the accuracy




SVM Classifier

## Motivation

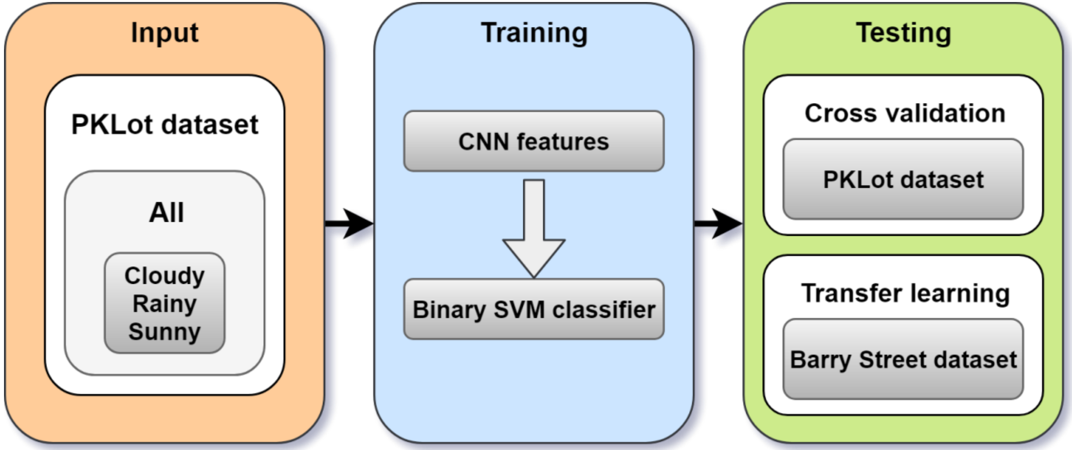
CNN-SVM systems yield best results with Handwriting detection *(Niu and Suen, 2012)* and pedestrian detection *(Szarvas et al., 2005*)

# Hypothesis and methodology

- **Hypothesis:** *"features extracted by a pre-trained CNN can be used directly to train an SVM classier for the detection of parking occupancy in a CCTV image sequence".*

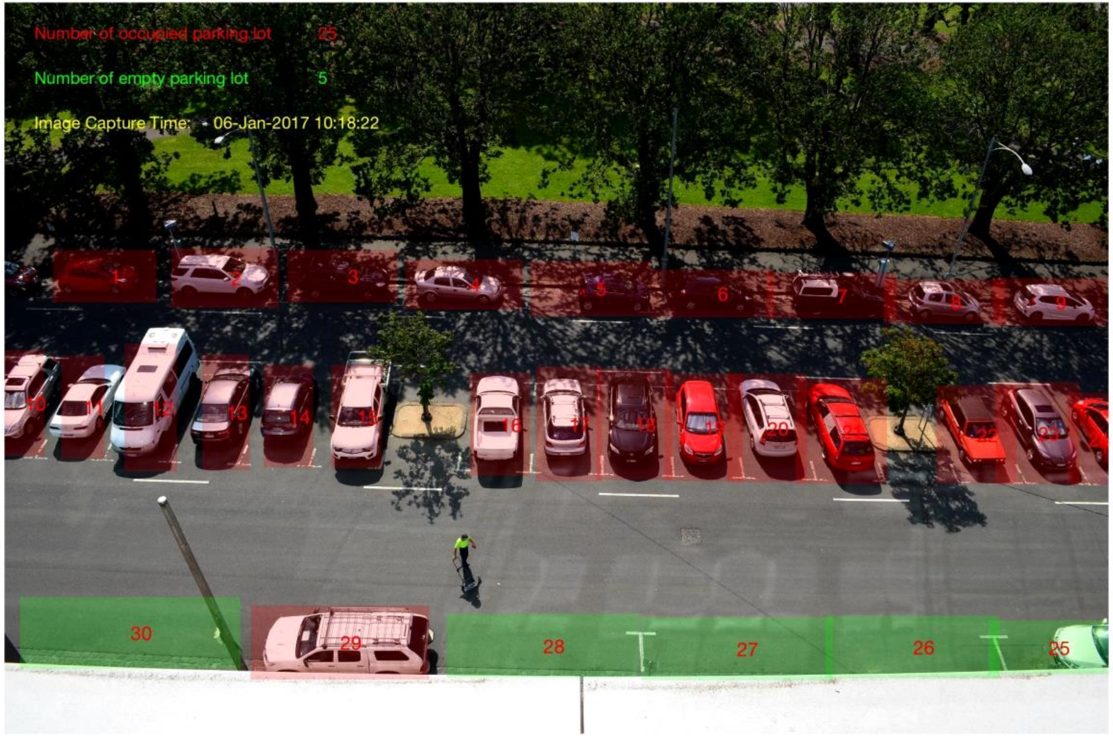

Public dataset (PKLot - *[de Almeida et al., 2015](#)* ).

Barry Street dataset for one day, having sunny to cloudy weather, created for evaluating transfer learning




A simplified layout of the framework

# Results: Video demo




**Processing speed (30 parking spots) - 2 seconds on 2.5GHz i5 processor.**

# Some more unfamiliar words!

**Sensitivity** = $\frac{TP}{TP+FN}$

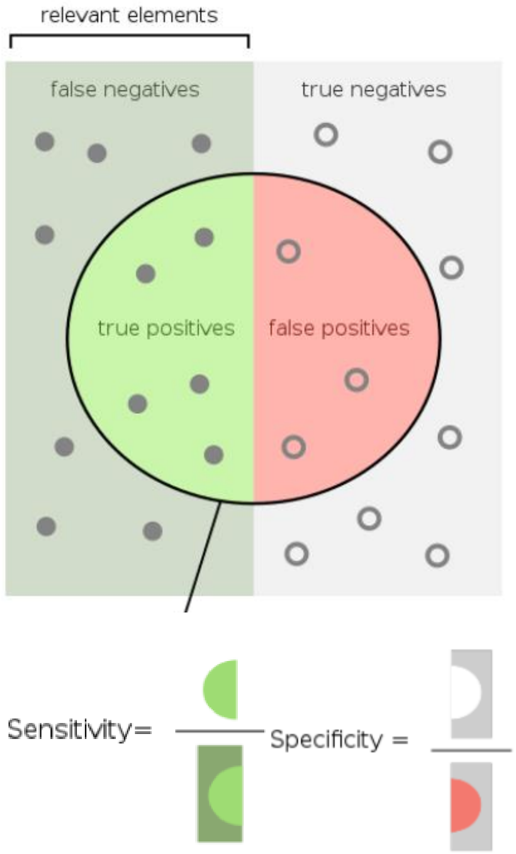
How many occupied spots identified as occupied

**Specificity** = $\frac{TN}{TN+FP}$

How many vacant spaces identified as vacant

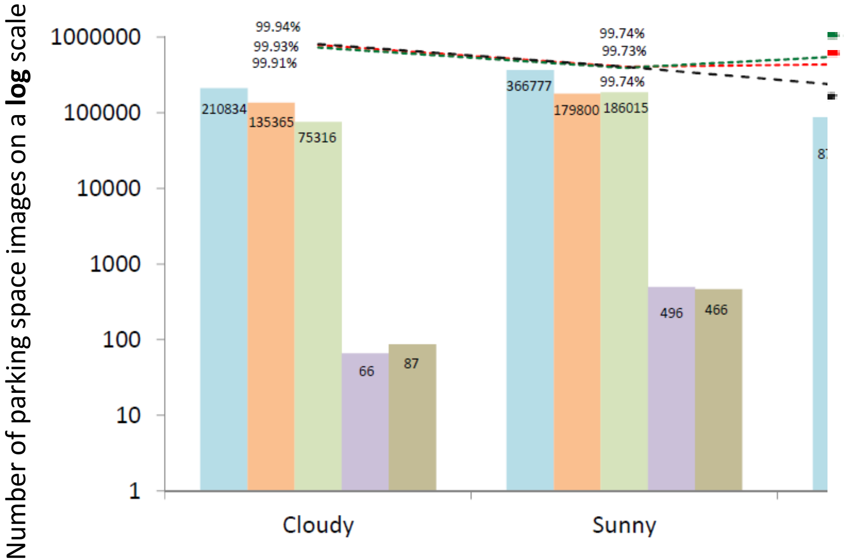
**Overall accuracy** = $\frac{TP+TN}{TP+TN+FN+FP}$

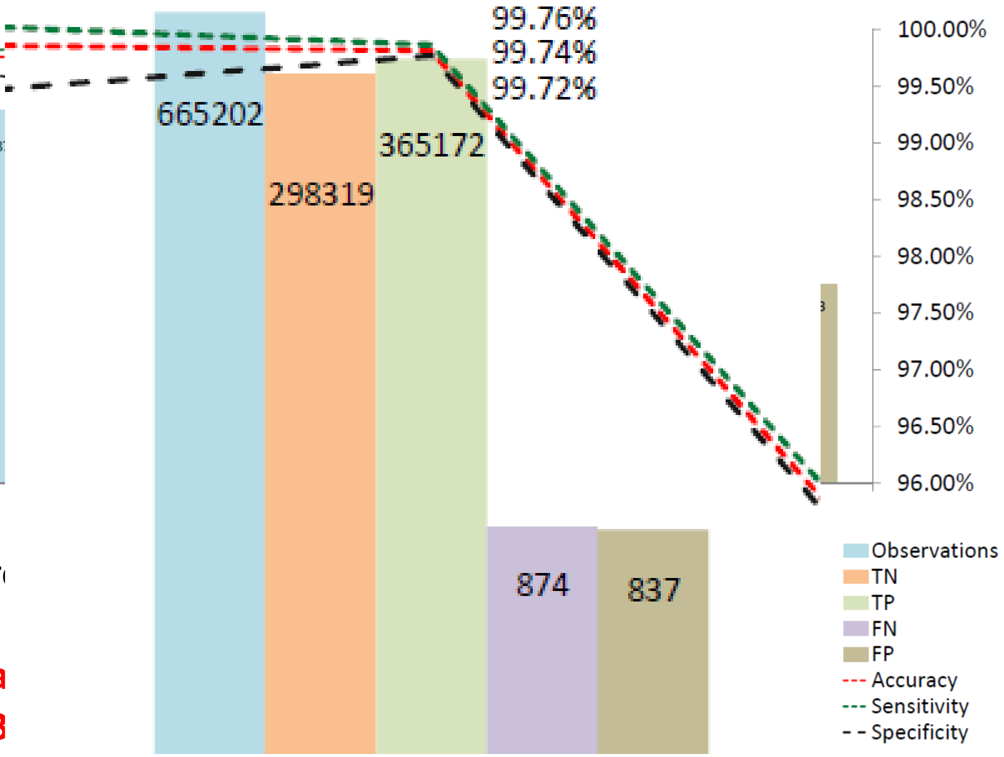
How many parking spot occupancy correctly identified




**TN** –True Negative, **TP** – True Positive, **FN** – False Negative, **FP** – False Positive

# Results: Accuracy

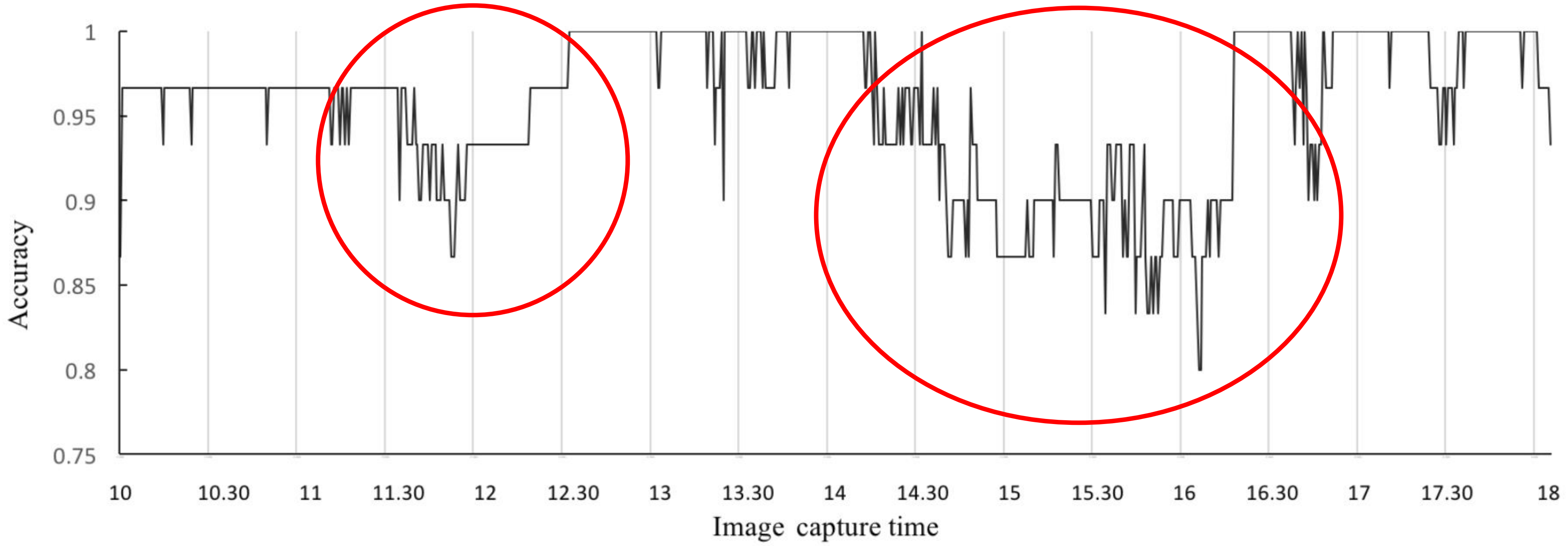



The classification r

Overall accuracy: **99.7 % (PKLot data**
Transfer learning accuracy: **96.6 % (B**

# Results: Correlation with time




The classification accuracy of Barry street images by the time of the day.

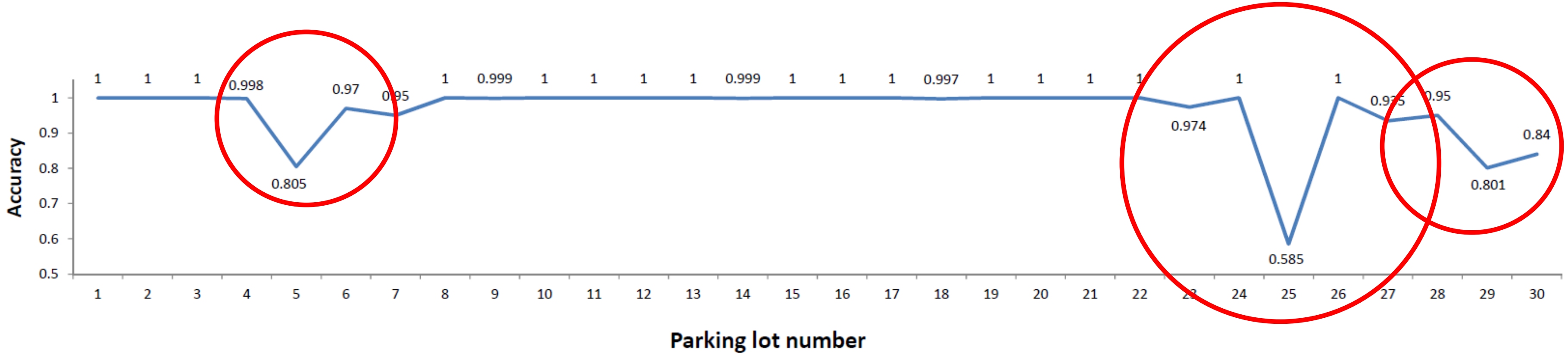
# Discussion: Correlation with time

Time: 16:25 Hrs


Effects of building shadows on the parking spaces.

Effects of change in occupancy

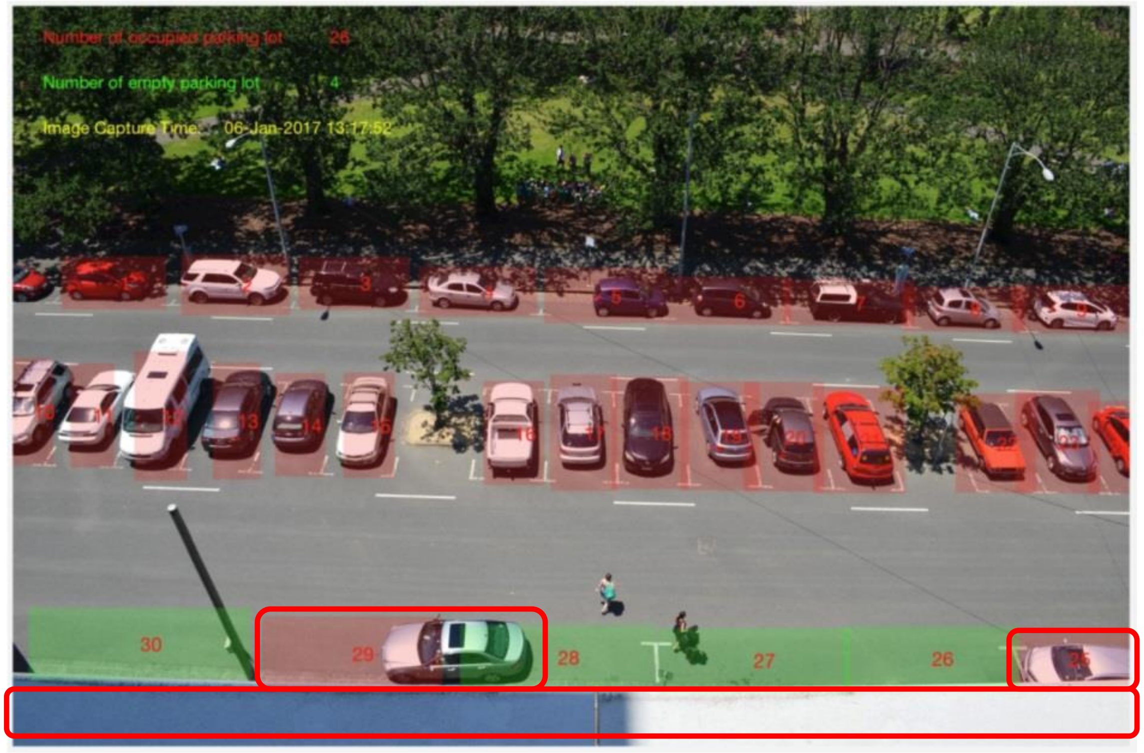
# Results: Correlation with parking spots




The variation of the accuracy over the whole period by the parking space number.

# Discussion: Correlation with parking spots

Time: 13:17 Hrs




Occlusion by wall

Ambiguity of parking spaces

Occlusion due to no visibility

# Discussion: Correlation with parking spots


Misclassification for plot no. 5

# Room for improvement

Removing bias of training

Effects of shadows and solar reflection – image normalisation

Low-end cheap Graphics Processing Units (GPUs)

Parking space ambiguity – dynamic segmentation

# Potential for commercialisation

## Recommendation

- Location specific model training
- better understanding of the environment

## Requirements

- Image data of all weather conditions
- Manually labelled occupancy details

## Expected result

- Accuracy >99.7%

# Conclusion

## Pros

Cost effective

On street parking

## Cons


CCTV coverage

Visibility

## Future works


Night lighting

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Questions?

Thank you for your kind attention