Deep Learning and Spatial Statistics for determining Winter Road Surface Condition

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Source: thestar.com

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Agenda

1. Introduction
2. Data integration
3. Automated determination of Winter Road Condition
4. Conclusions

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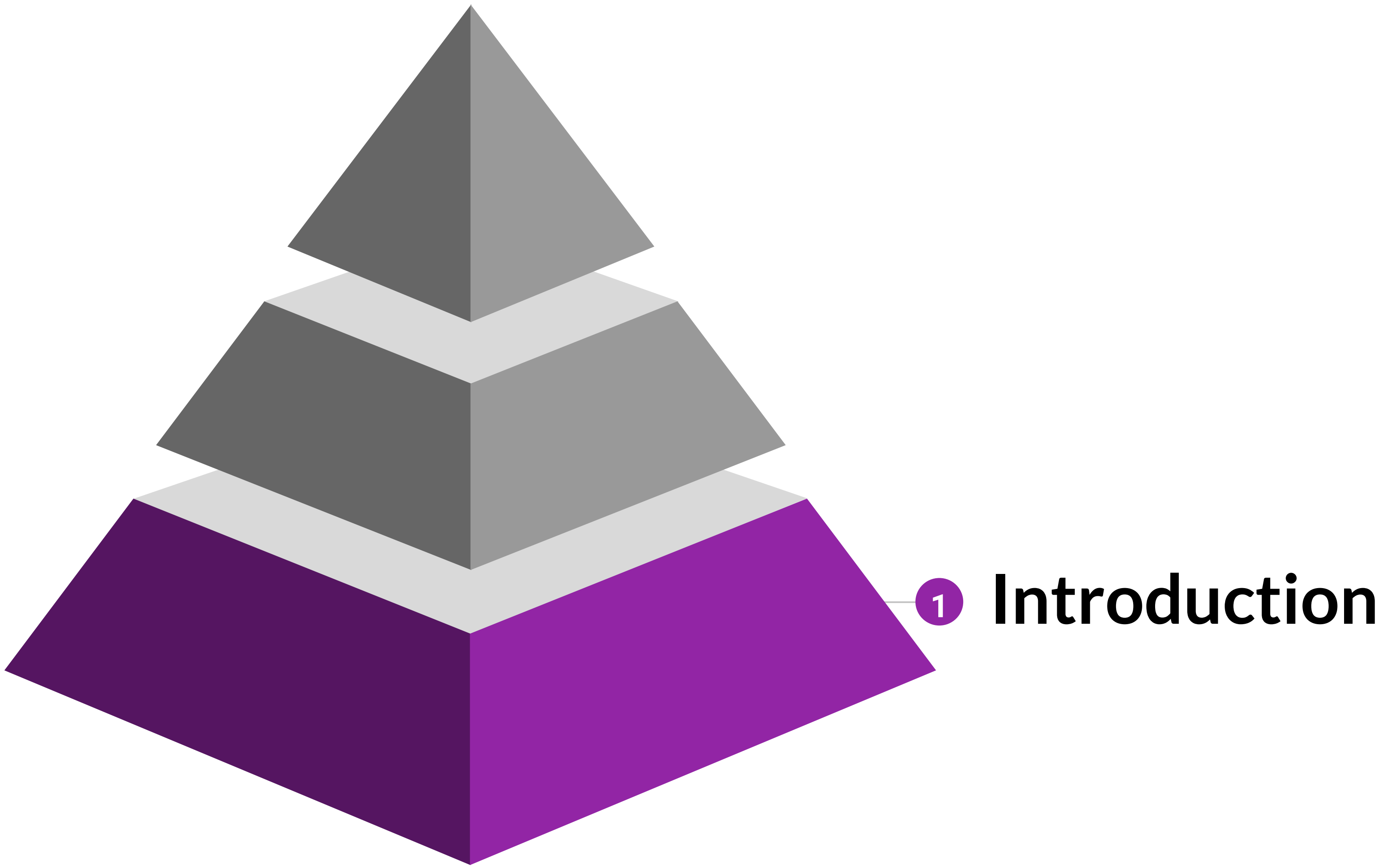

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Winter road maintenance: Safety and resource optimization

tar Edition
LOCATION

THE STAR

CANADA POLITICS WORLD OPINION LIFE SPORTS ENTERTAINMENT BUSINESS STAR INVE

Ontario British Columbia Alberta Quebec Nova Scotia

Ontario's winter roads 'less safe' since privatization: auditor

By Rob Ferguson Queen's Park Bureau
Wed., April 29, 2015

Ontario. 50% of the total highway maintenance budget is spent on winter maintenance operations. *MTO*

Toronto. Annual budget of $90 million to ensure that roads and sidewalks are clear and safe during the winter. *theweathernetwork.com*

Ottawa. The budget for winter operations in 2018 was $68.3 million, $2.3-million more than the previous year. *OttawaCitizen.com*

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Winter road conditions

MINISTRY OF TRANSPORTATION Ontario

Road is bare
All wheels of a vehicle
are on a bare surface.

Road is partly covered
Two wheels of a vehicle
are on a bare surface.

Road is covered
All wheels of a vehicle
are on snow or ice.

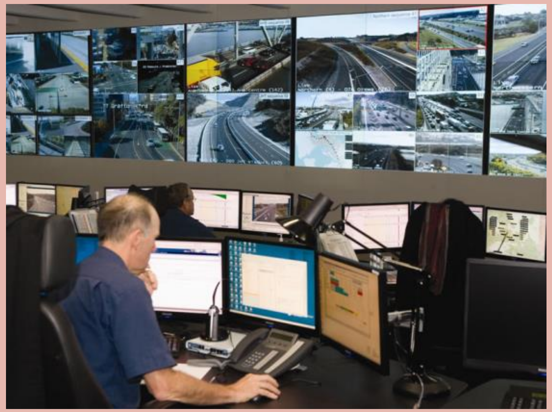
Winter road maintenance: Current approach

Road Weather Information Systems (RWIS)

Road patrolling visual inspection

Limited geographic coverage

Visual monitoring



Data-intensive process
Automation needed

Resource allocation

Research goals

1. Evaluate the integration of additional sources of data to increase geographic coverage of Winter road monitoring

2. Compare Deep Learning models for automated classification of Road Surface Condition (RSC) from roadside camera images and weather data

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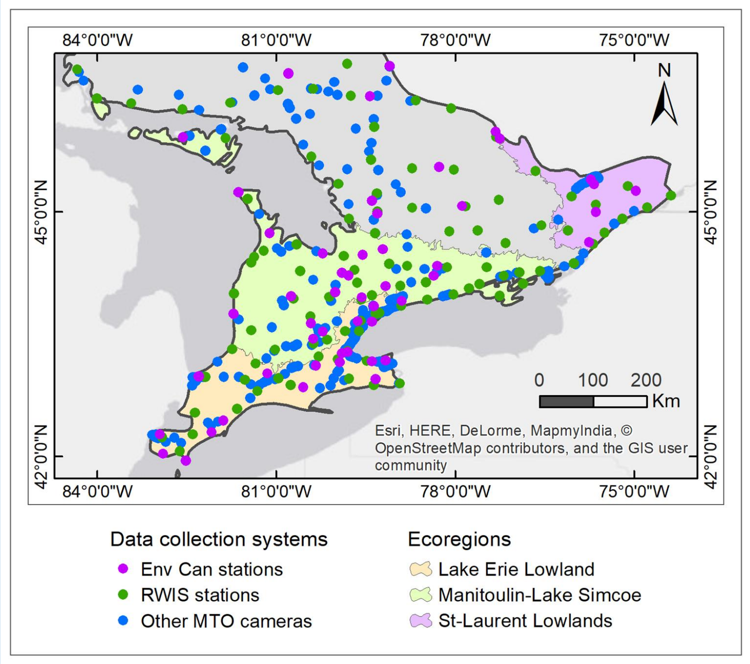
Winter road maintenance: Suggested approach

Add **6x** more input data

(RWIS) + other MTO Cams + Env. Can Weather



Automated monitoring

Efficient decision making

Deep Learning for detecting road surface condition

Evaluate & improve

Better resource allocation, improved operations

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Integration of roadside camera images and weather data for monitoring winter road surface conditions

Placed 1st in this year's CARSP Student Paper Competition

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Road Weather Information System (RWIS)

Image source

139 stations
in Ontario

Image source

- Roadside camera
- Weather sensors
- Embedded pavement sensors

Station NWR-06

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Other MTO camera stations

- ✅ Roadside camera
- ❌ Weather sensors
- ❌ Embedded pavement sensors

Image source

439 cameras
in Ontario

Environment Canada weather stations

- ❌ Roadside camera
- ✅ Weather sensors
- ❌ Embedded pavement sensors

Image source

99 stations in Ontario

Image source

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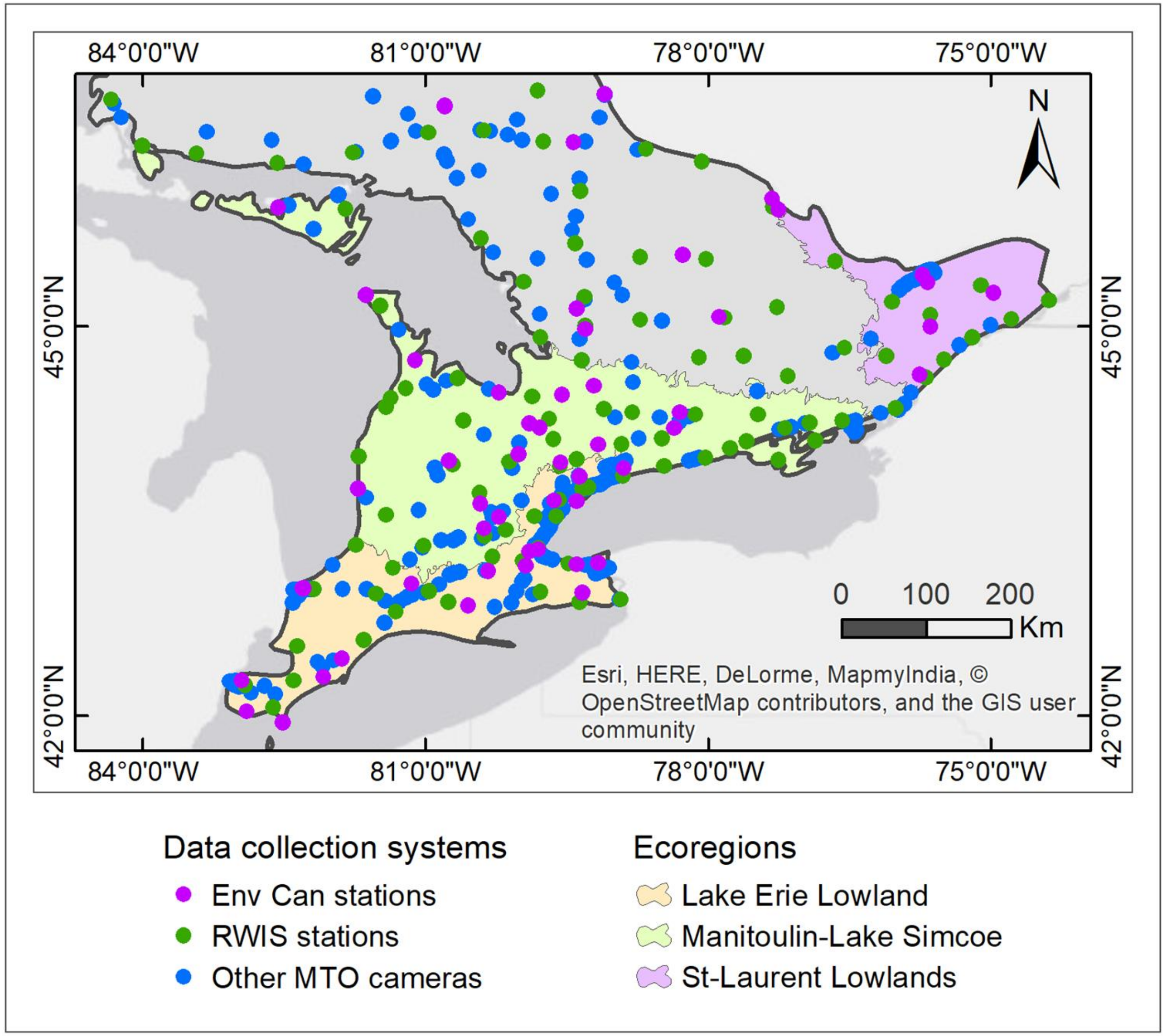
Area of study

Ecoregion	Population density inhabitants/km²	Rank across Canada
Lake Erie Lowland	344	2nd
St. Lawrence Lowlands	179	3rd
Manitoulin-Lake Simcoe	66	6th

Table 1. The three most densely inhabited ecoregions in Southern Ontario, StatCan 2016.



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Nearest neighbor NN

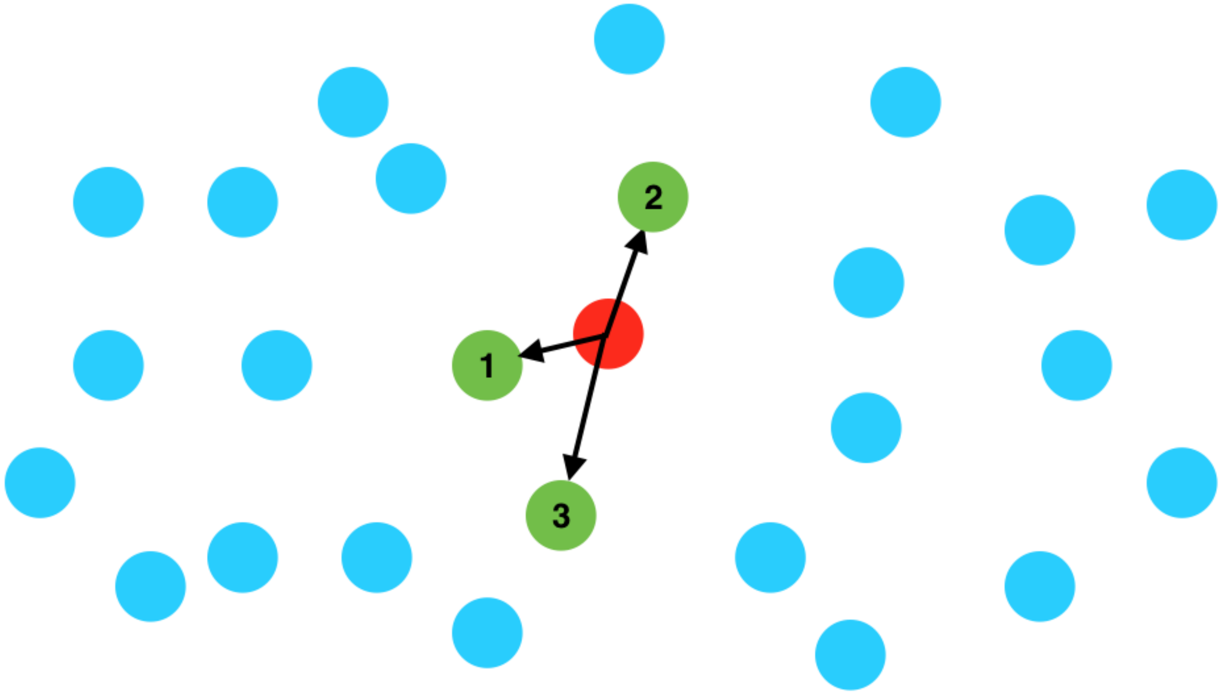


Image source

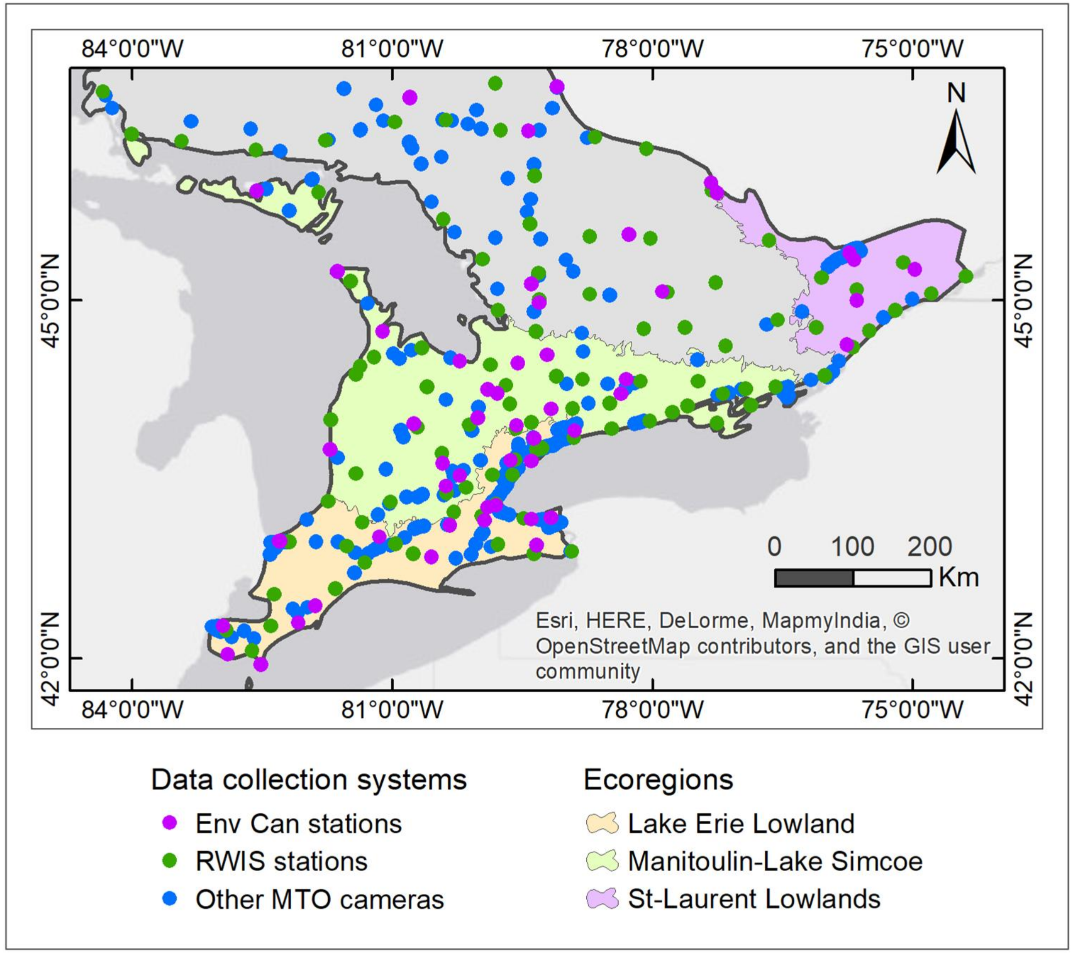
Nearest neighbor NN analysis

Type	# of locations in Ontario	Avg. distance to NN (km)	# of locations in three populous ecoregions
RWIS	139	38.4	68
Other MTO	439	7.2	364
RWIS + MTO	578	9.4	432

Table 2. Adding other MTO roadside cameras to increase the number of images.

Type	# of locations in Ontario	Avg. distance to NN (km)	# of locations in three populous ecoregions
RWIS	139	38.4	68
Env. Canada	99	35.8	45
RWIS + Env. Can	238	25.7	113

Table 3. Adding Environment Canada stations to interpolate weather data.



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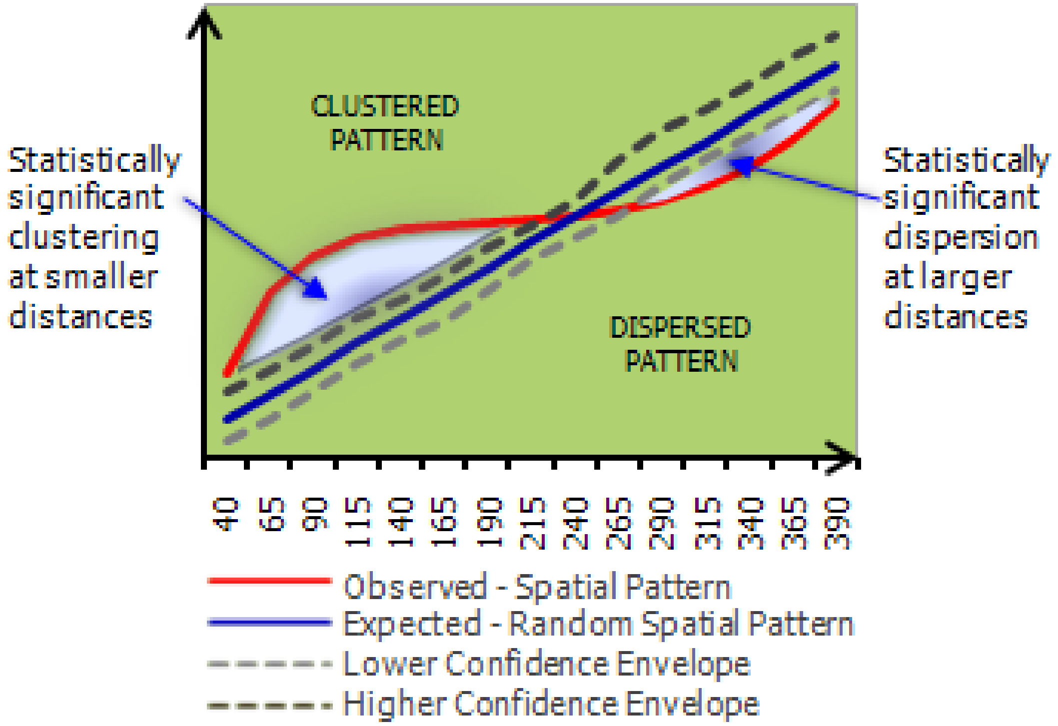
K-Function



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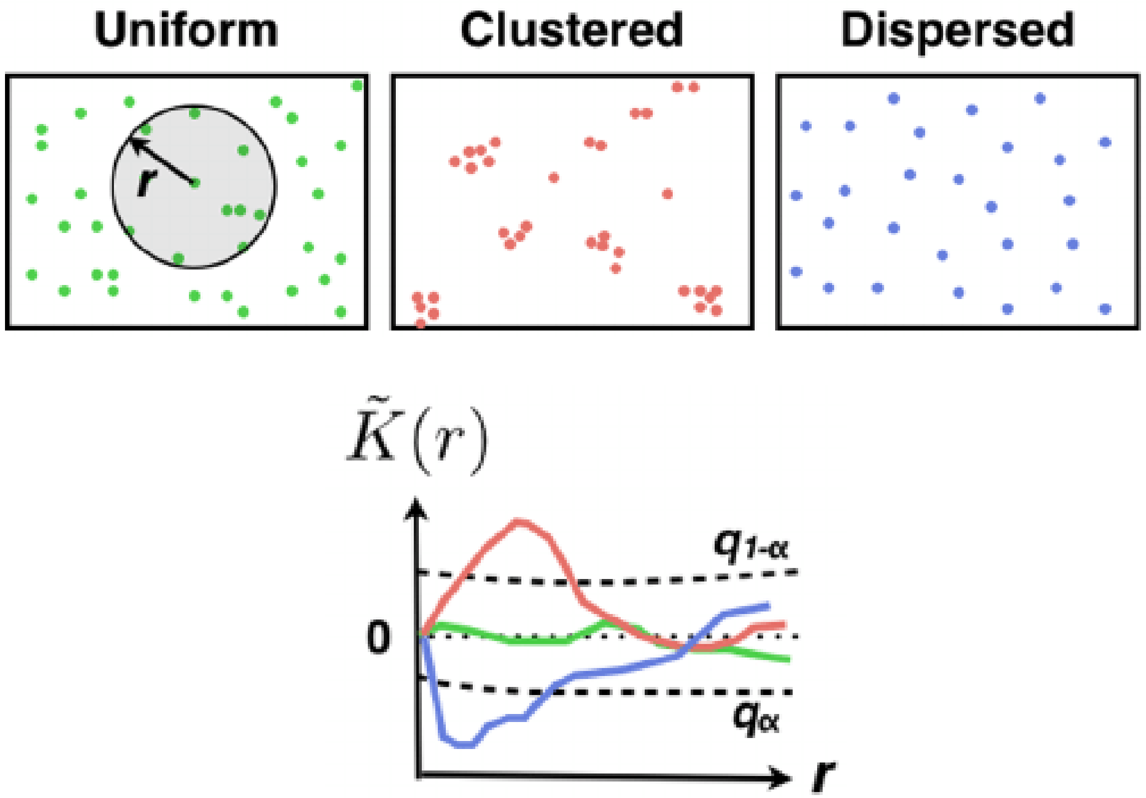

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L-Function analysis

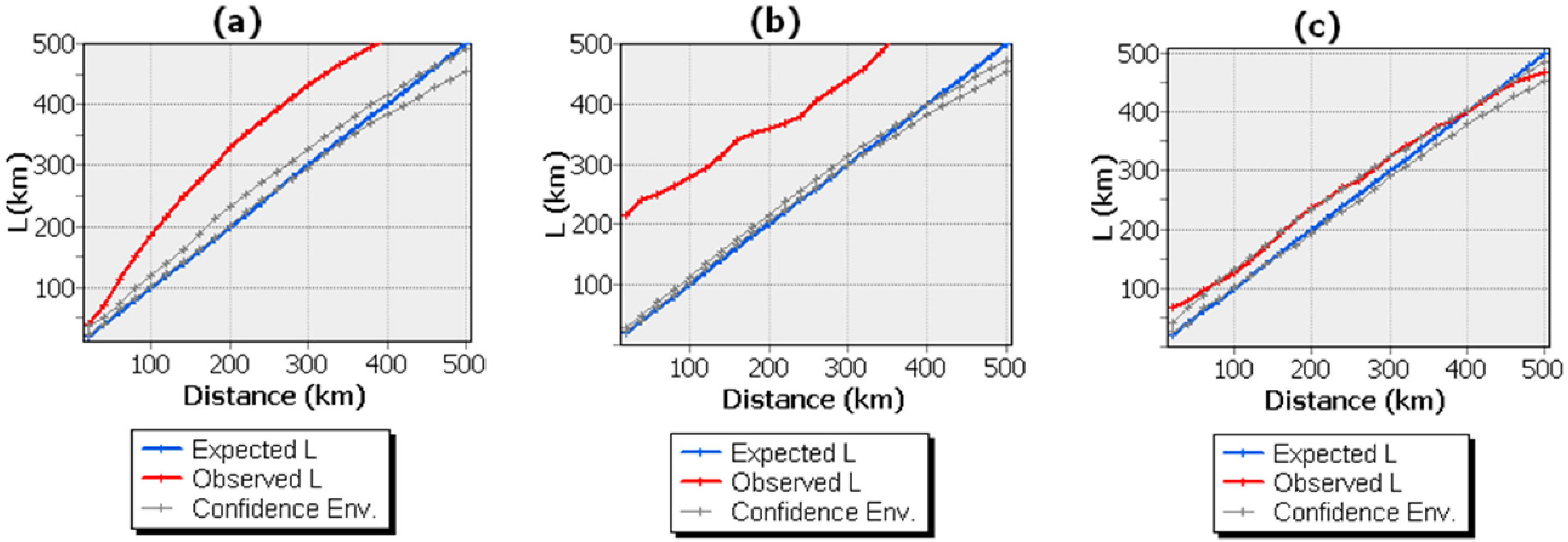

Figure 3. Multi-distance spatial cluster (L-Function) plots for: (a) RWIS stations, (b) other MTO cameras, and (c) Environment Canada stations.

Weather interpolation for all other MTO cameras

Sample of weather data

- 40 RWIS + 40 Env. Canada = 80 stations
- Three weather variables
- No-snow and snowy days
- 480 observations in total

✔ Roadside camera
✘ Weather sensors
✘ Embedded pavement sensors

Summary statistics	T1 - No snow - 2017/11/07 08:00			T2 - Snow - 2017/12/25 08:00		
	air temp. (°C)	wind speed (km/h)	pressure (kPa)	air temp. (°C)	wind speed (km/h)	pressure (kPa)
Mean	-1.921	4.912	99.950	-12.186	13.587	98.518
Std. dev.	5.195	6.419	2.809	9.509	11.128	2.782
CV%	-----------	131%	3%	-----------	82%	3%

Table 4. Summary statistics of three weather variables for a no-snow day and a snowy day.

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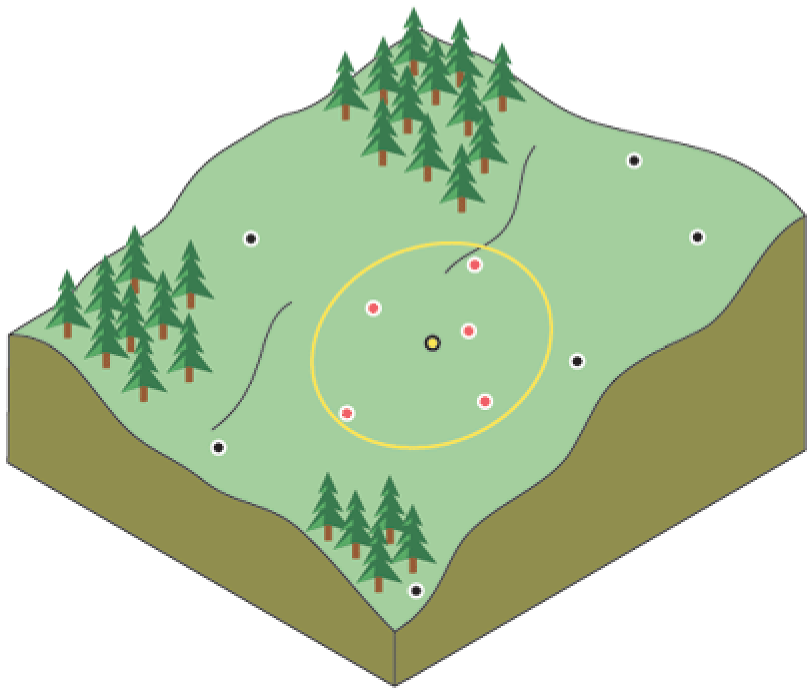
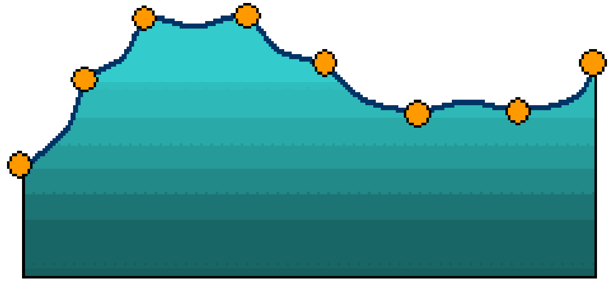
Spatial statistics: Interpolation methods

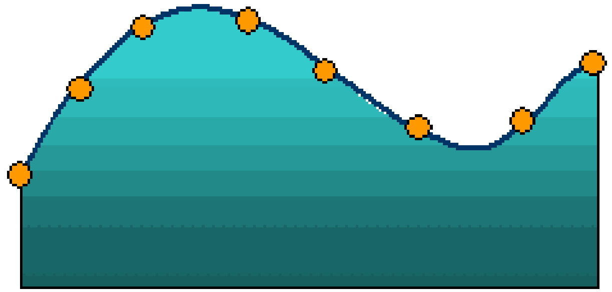


Neighborhood for selected point

Image source



Example Inverse Distance Weighted (IDW) profile



Example Radial Basis Function (RBF) profile

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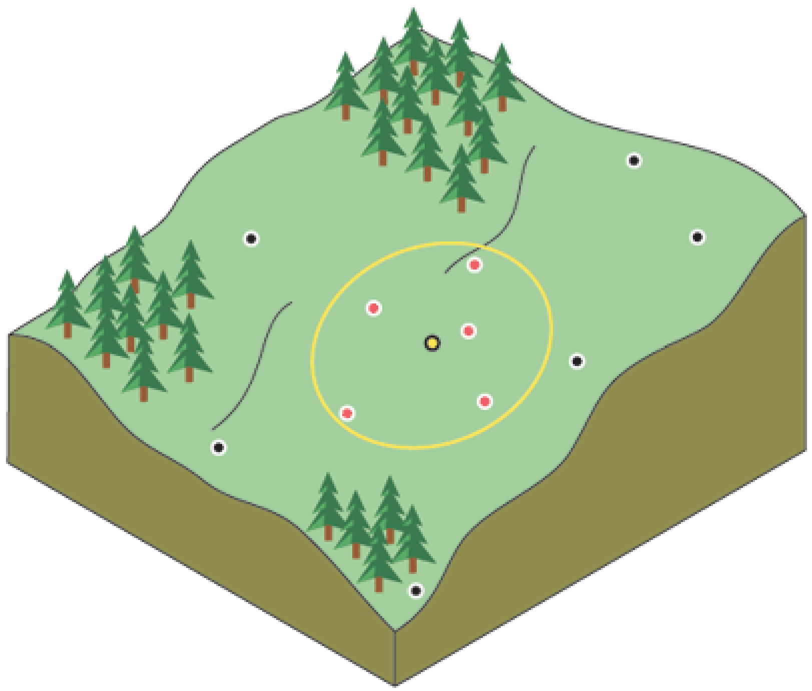
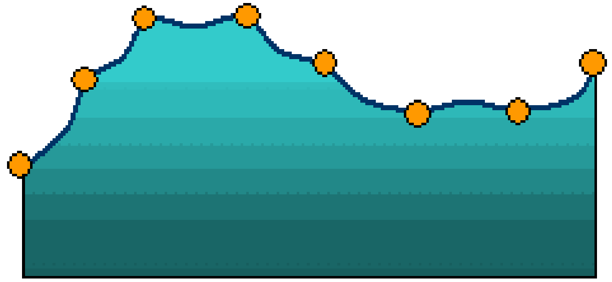
Intermediate slide here

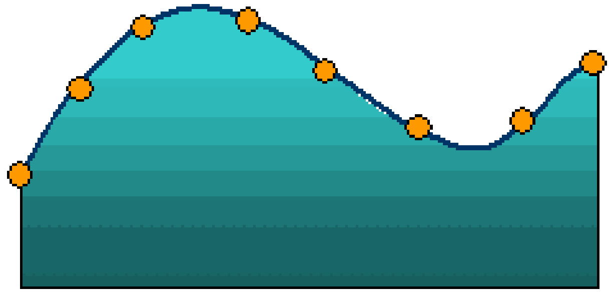


Neighborhood for selected point

Image source



Example Inverse Distance Weighted (IDW) profile



Example Radial Basis Function (RBF) profile

Weather interpolation for all other MTO cameras

Interpolation methods

- Inverse distance weighted (IDW)
- Radial Basis Function (RBF)
- Ordinary Kriging (OK)

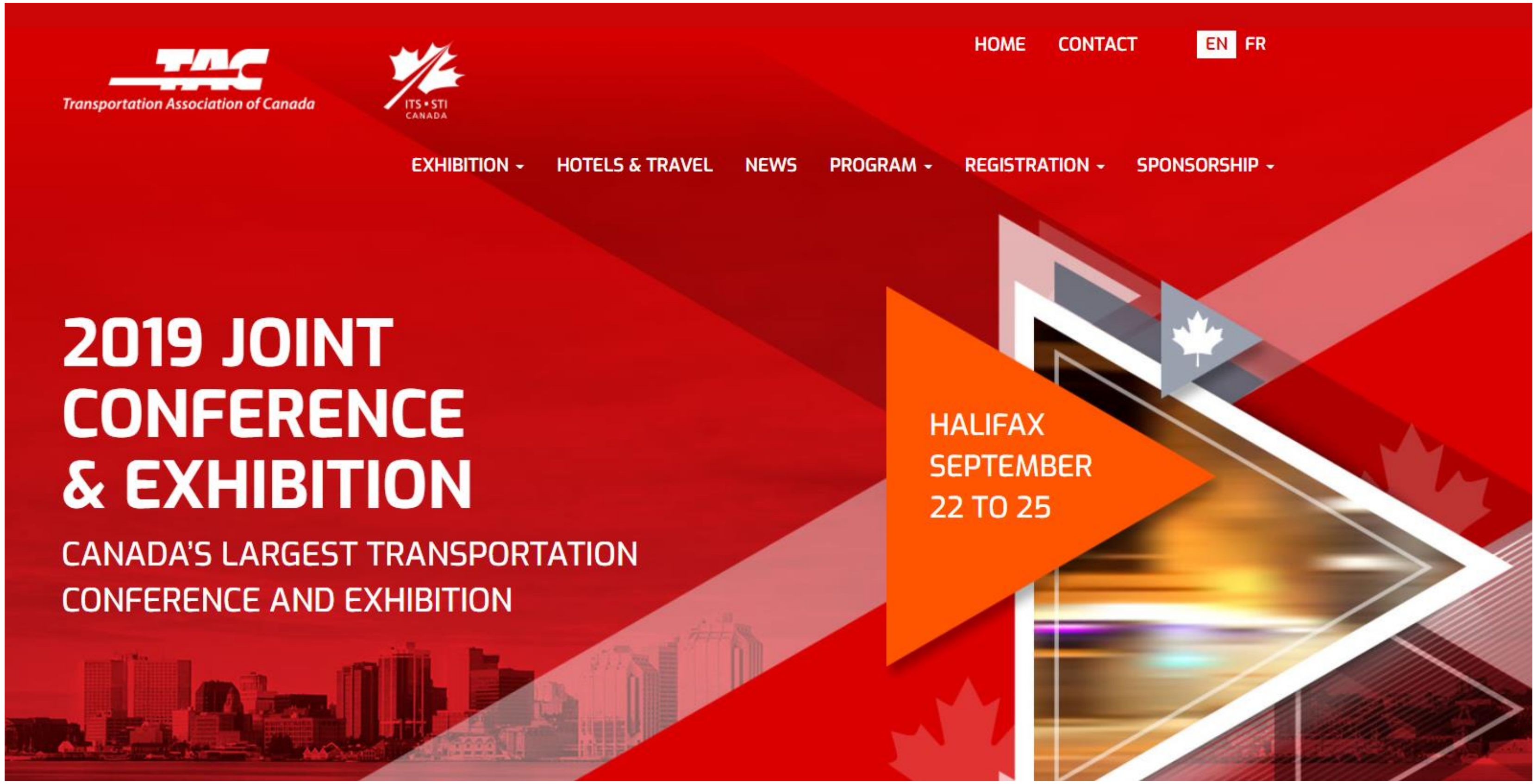
✓ Roadside camera
✗ Weather sensors
✗ Embedded pavement sensors

Interpolation Method	T1 - No snow - 2017/11/07 08:00			T2 - Snow - 2017/12/25 08:00		
	Air temp. (°C)	Wind speed (km/h)	Pressure (kPa)	Air temp. (°C)	Wind speed (km/h)	Pressure (kPa)
IDW	2.054	6.073	3.094	4.139	8.761	3.053
RBF	1.971	6.156	3.001	**3.898**	8.718	**2.963**
Ord. Kriging	**1.868**	**5.660**	**2.992**	3.921	**8.654**	2.999

Table 5. Root Mean Square of three interpolation methods applied on a no-snow and snowy day.

Automated determination of Winter Road Condition

Comparison of Deep Learning models for Determining Road Surface Condition from Roadside Camera Images and Weather Data



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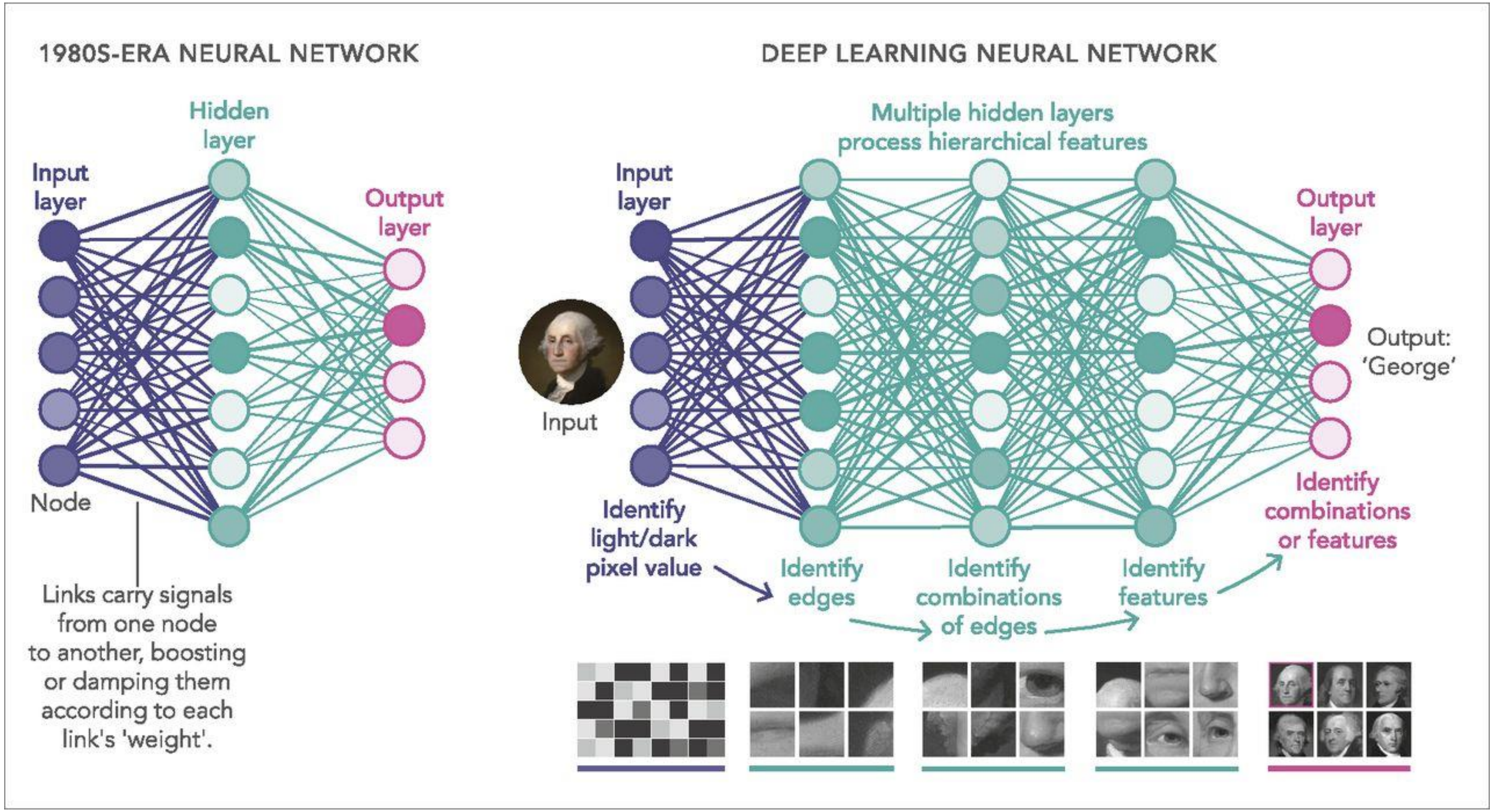
Why "Deep" Learning?



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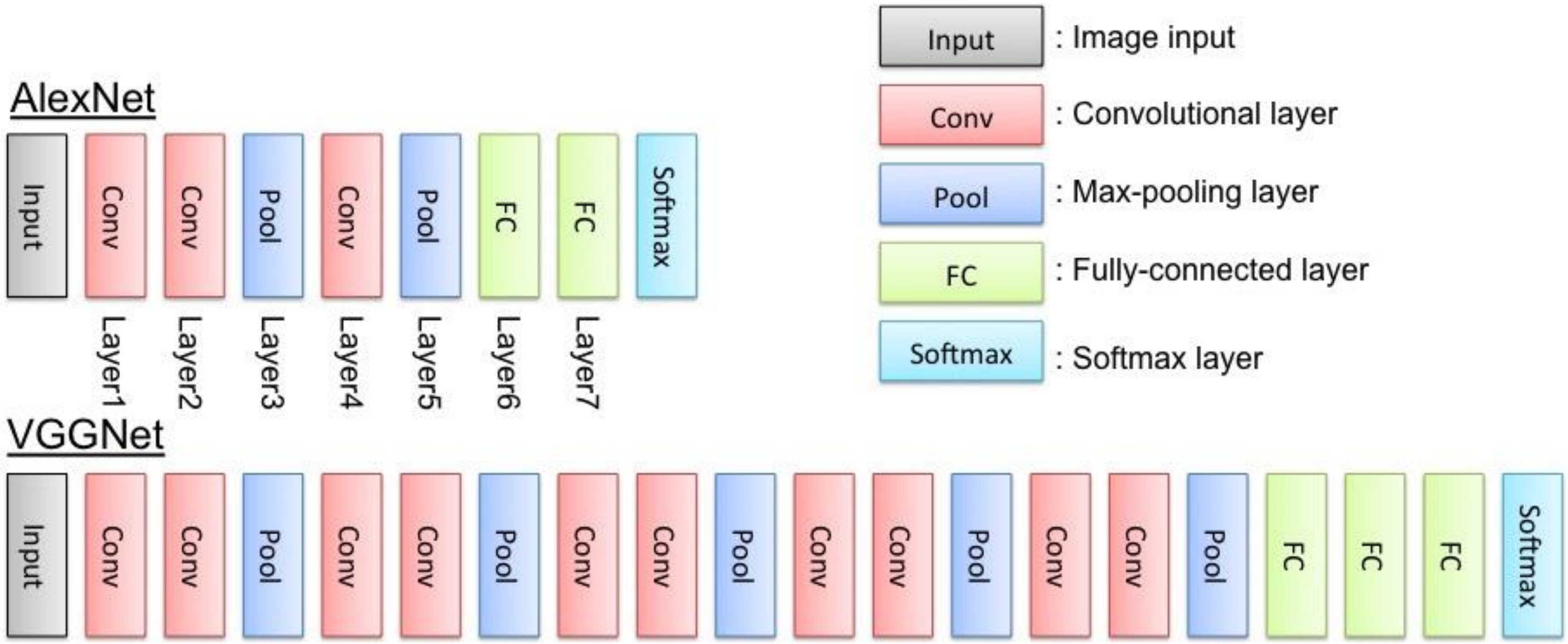
Baseline Deep Learning models for image classification



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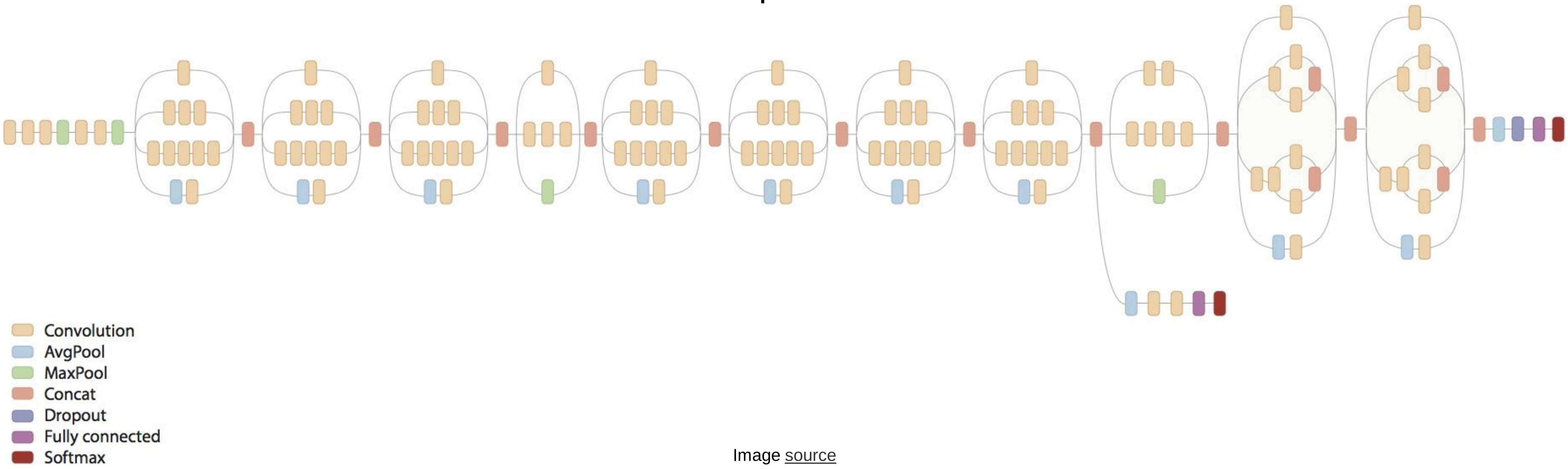
Advanced Deep Learning model for image classification

Inception V3



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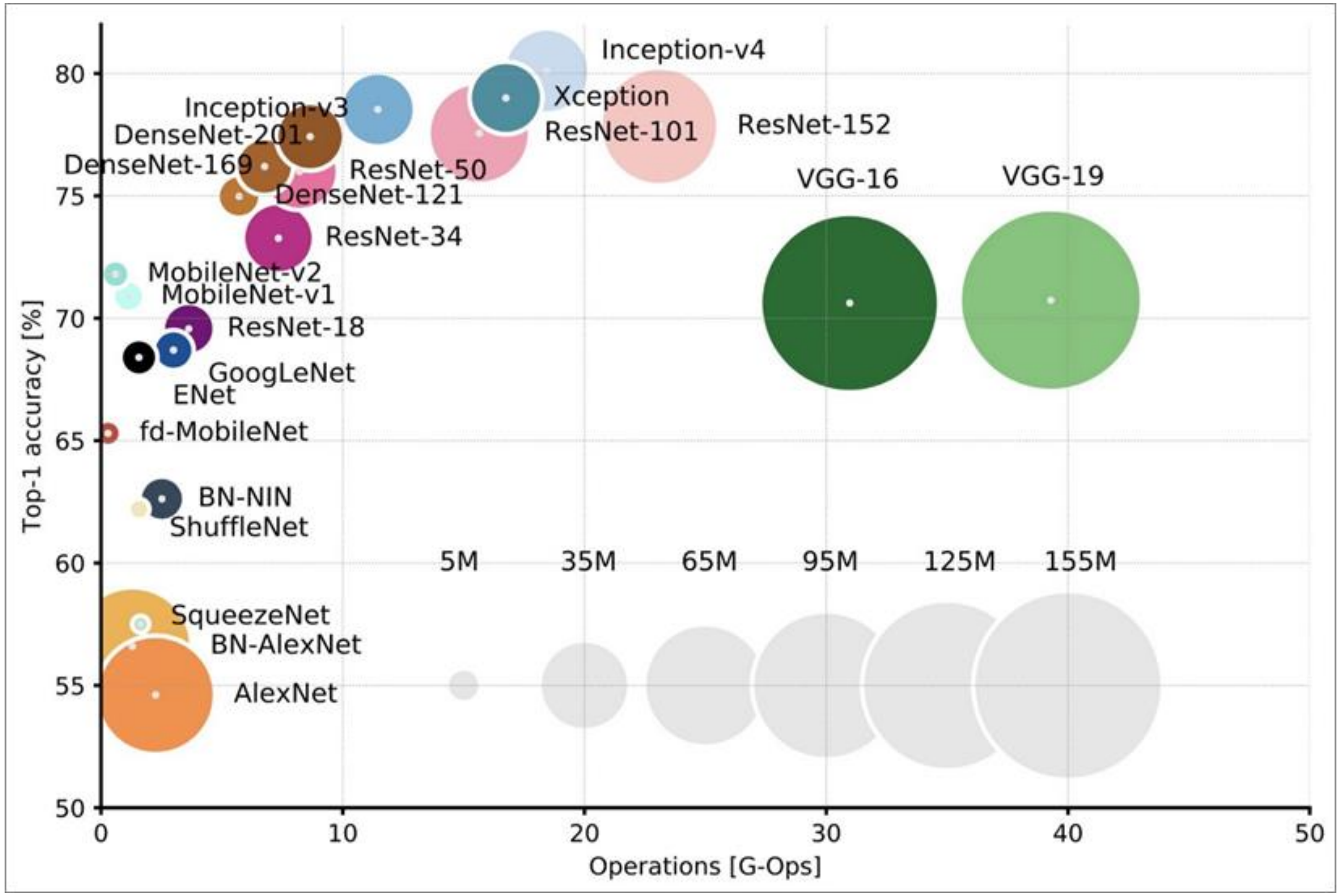
Computation cost versus accuracy



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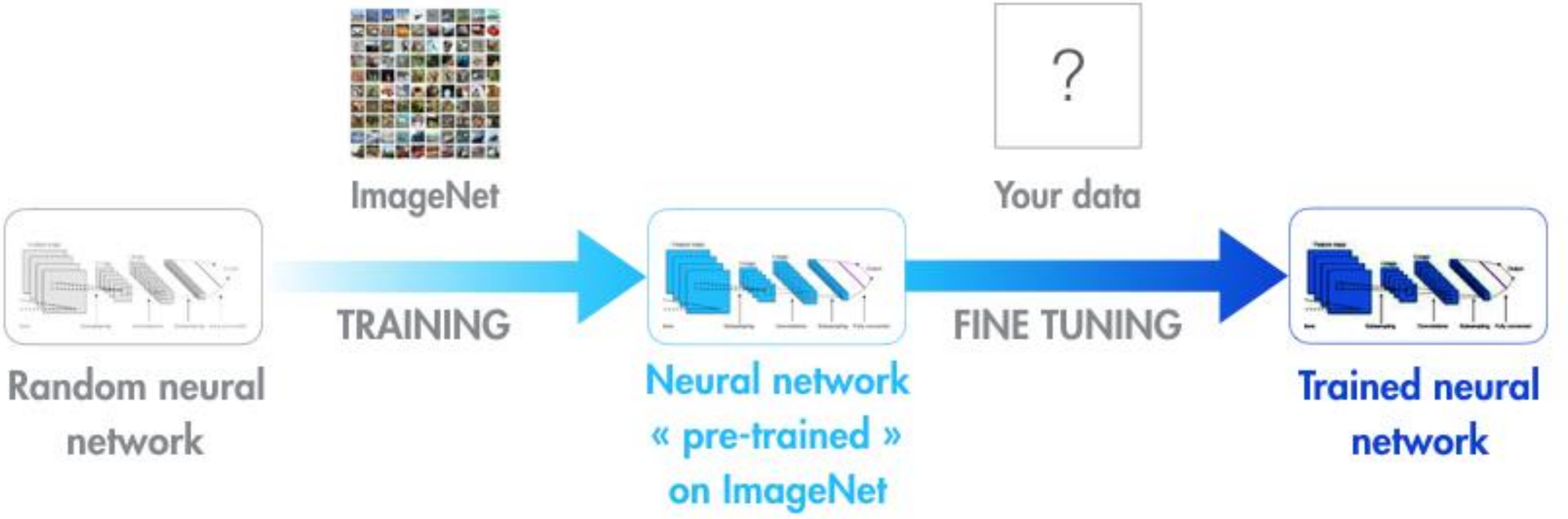
Transfer learning



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Previous research

Title	Year	Data source	Method
Evaluation of Alternative Pre-trained Convolutional Neural Networks for Winter RSC Monitoring	2018	Dash and roadside camera	Pre-trained DNN
Winter Road Surface Condition Recognition Using a Pre-trained Deep CNN	2018	Dash camera	Pre-trained DNN
Connected Vehicle Solution for Winter Road Surface Condition Monitoring	2016	Dash camera	ANN RTrees RF
Winter Road Surface Condition Monitoring Field Evaluation of a Smartphone-Based System	2015	Dash camera	SVM
An automatic image recognition system for winter road surface condition classification	2010	Dash camera	SVM
Road Condition Imaging: Model Development	2015	Stations IR cam	Bayesian net
Road Surface Status Classification Using Spectral Analysis of NIR Camera Images	2015	Vehicle mounted NIR	KNN SVM NN
Road condition discrimination using weather data and camera images	2011	Stations IR cam	PCA between vars
Assessment of Deep Convolutional Neural Networks for Road Surface Classification	2018	Dash camera	ResNet Inception
Evaluating features and classifiers for road weather condition analysis	2016	Dash camera	Legacy image methods

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Image dataset

- 40 RWIS stations across Ontario
- 14.000 images in total
- 3 classes: bare, partial, and full snow cover

- 70% training
- 20% validation
- 10% testing

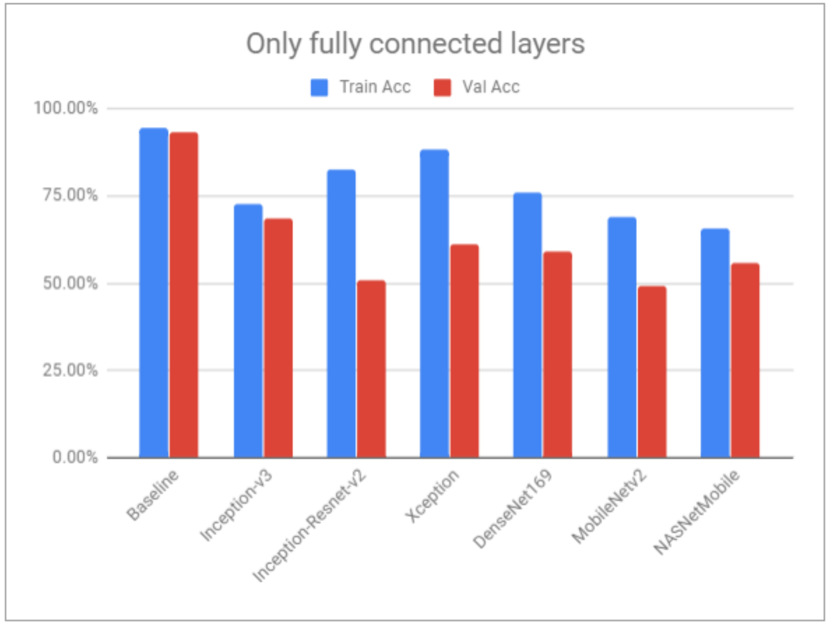
- Summary of images in the train/validation set -
Total images: 12600
Bare pavement 5691 Approx. 45%
Partial snow coverage 5114 Approx. 40%
Full snow coverage 1795 Approx. 14%

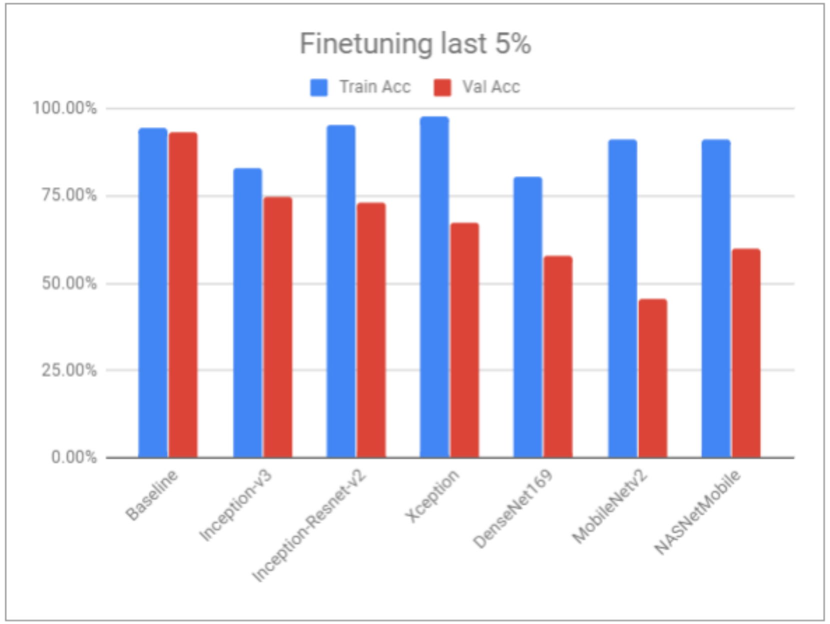
- Summary of images in the test set -
Total images: 1400
Bare pavement 648 Approx. 46%
Partial snow coverage 558 Approx. 39%
Full snow coverage 194 Approx. 13%

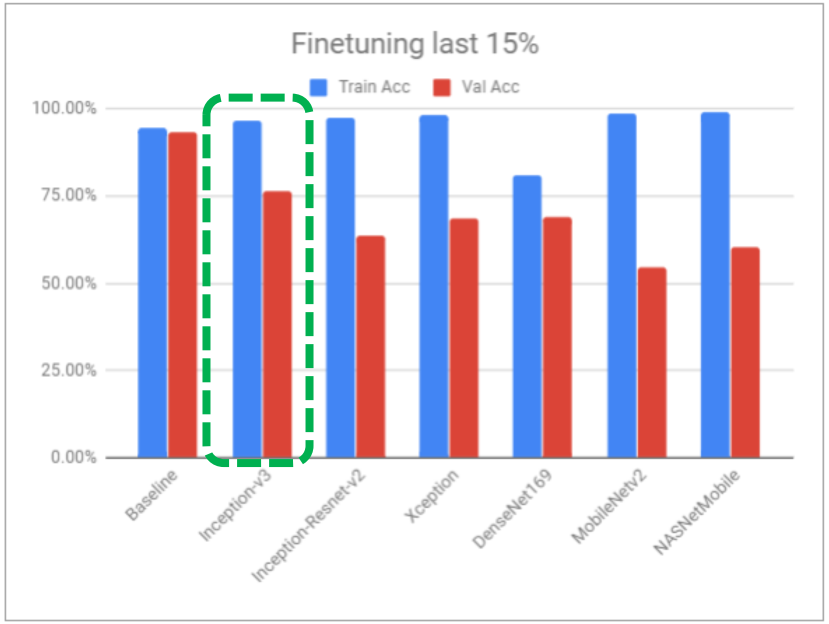
Model comparison: Fine-tuning pretrained models

- Optimizer SGD
- Learning rate 0.001
- 50 epochs

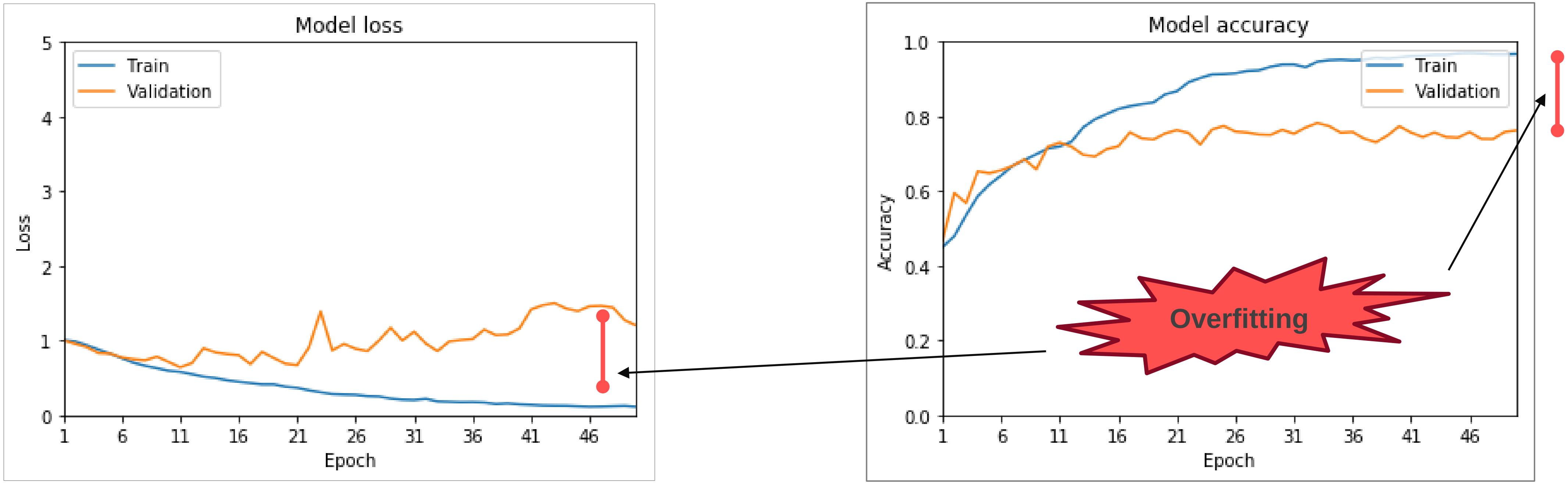
	Base model (Conv.)		Complete model		Fully connected		Finetuning last 5%		Finetuning last 15%	
Model	# Parameters	# Layers	# Parameters	# Layers	Train Acc	Val Acc	Train Acc	Val Acc	Train Acc	Val Acc
Baseline	392,608	10	996,019	17	**94.32%**	**93.06%**	**94.32%**	**93.06%**	**94.32%**	**93.06%**
Inception-v3	21,802,784	311	28,095,539	318	72.71%	68.65%	82.88%	74.88%	96.73%	76.27%
Inception-Resnet-v2	54,336,736	780	59,056,627	787	82.73%	50.95%	95.16%	73.17%	97.33%	63.77%
Xception	20,861,480	132	30,693,179	139	88.18%	61.15%	97.60%	67.42%	98.04%	68.41%
DenseNet169	12,642,880	595	16,557,907	602	75.95%	59.13%	80.60%	57.78%	81.08%	69.09%
MobileNetv2	2,257,984	155	2,320,723	162	68.87%	49.01%	91.01%	45.67%	98.59%	54.44%
NASNetMobile	4,269,716	769	4,321,703	776	65.53%	55.83%	91.37%	60.04%	98.86%	60.20%







Fine-tuning pretrained Inception V3 model – last 15%



-- Evaluation over the train and validation datasets --
Final train accuracy: 96.73%
Final validation accuracy: 76.27%

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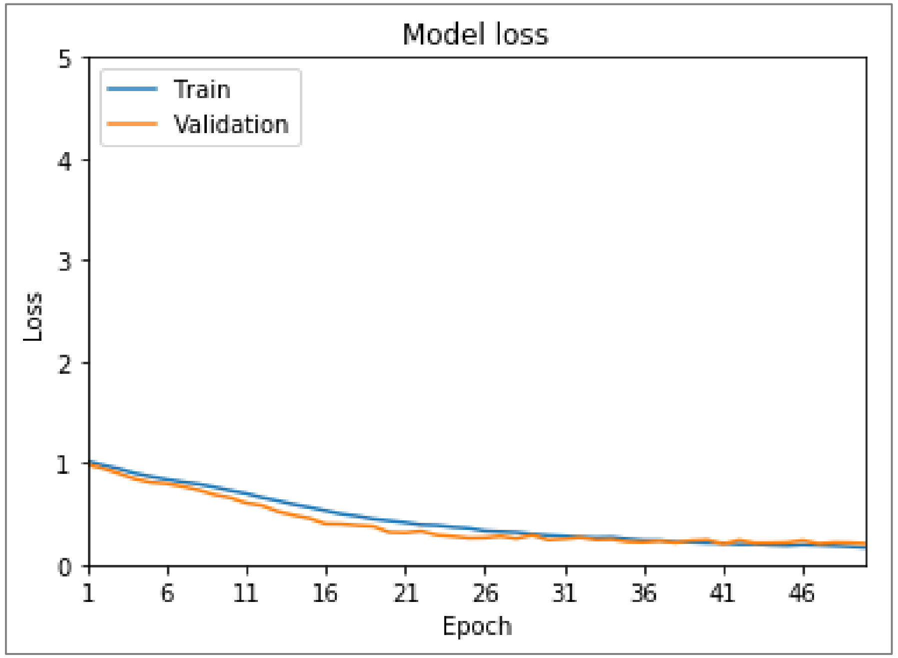
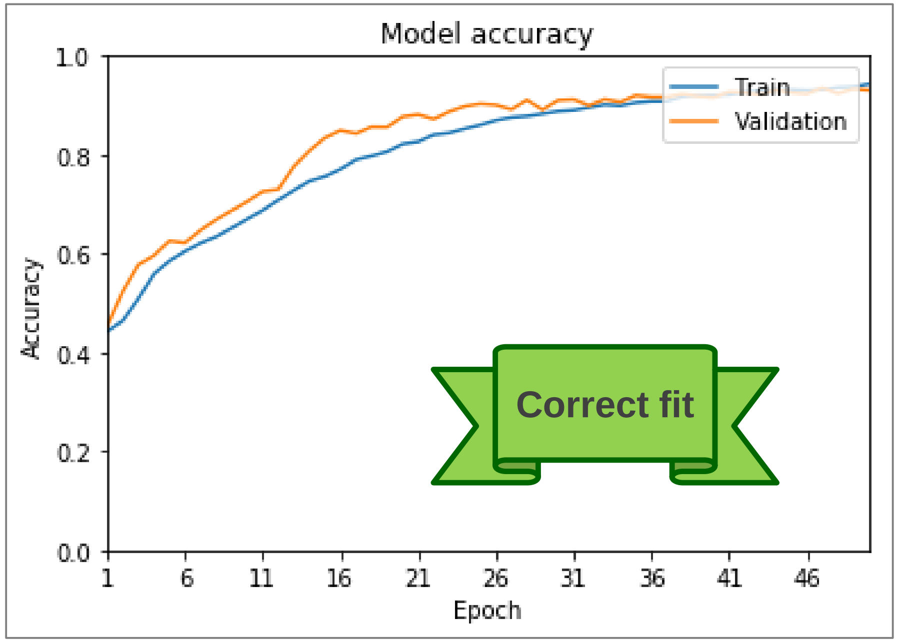
Baseline model – All layers trained from scratch





-- Evaluation over the train and validation datasets --

Final train accuracy: 94.32%

Final validation accuracy: 93.06%

Baseline model – Architecture

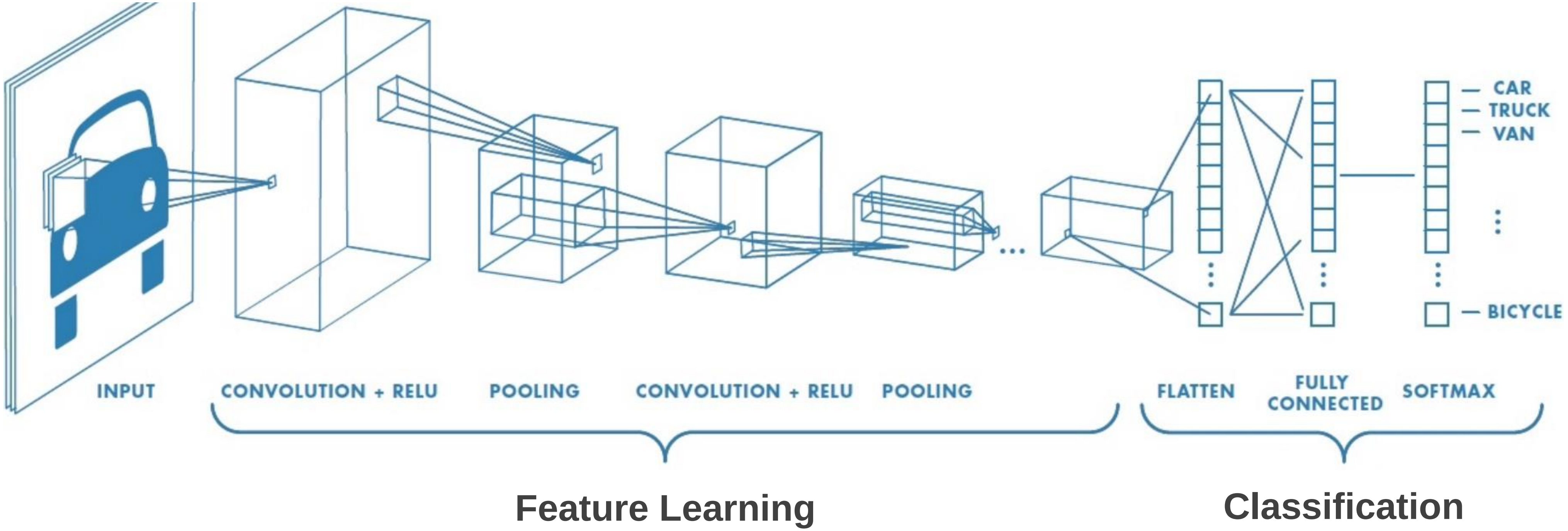


Image source

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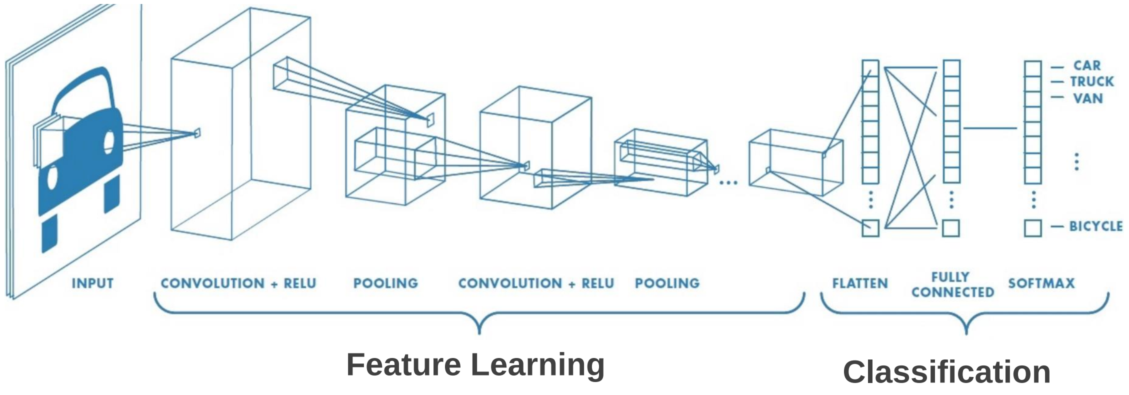
Baseline model – Architecture

Feature Learning

(Conv2D(16, kernel_size=(3, 3), activation='relu’, input_shape=(299, 299, 3)))
(MaxPooling2D(pool_size=(2, 2)))
(Conv2D(32, kernel_size=(3, 3), activation='relu'))
(MaxPooling2D(pool_size=(2, 2)))
(Conv2D(64, kernel_size=(3, 3), activation='relu'))
(MaxPooling2D(pool_size=(2, 2)))
(Conv2D(128, kernel_size=(3, 3), activation='relu'))
(MaxPooling2D(pool_size=(2, 2)))
(Conv2D(256, kernel_size=(3, 3), activation='relu'))
(MaxPooling2D(pool_size=(2, 2)))

Classification

(Dropout(0.5))
(Flatten())
(Dense(48, activation='relu'))
(Dropout(0.5))
(Dense(24, activation='relu'))
(Dropout(0.5))
(Dense(3, activation='softmax'))



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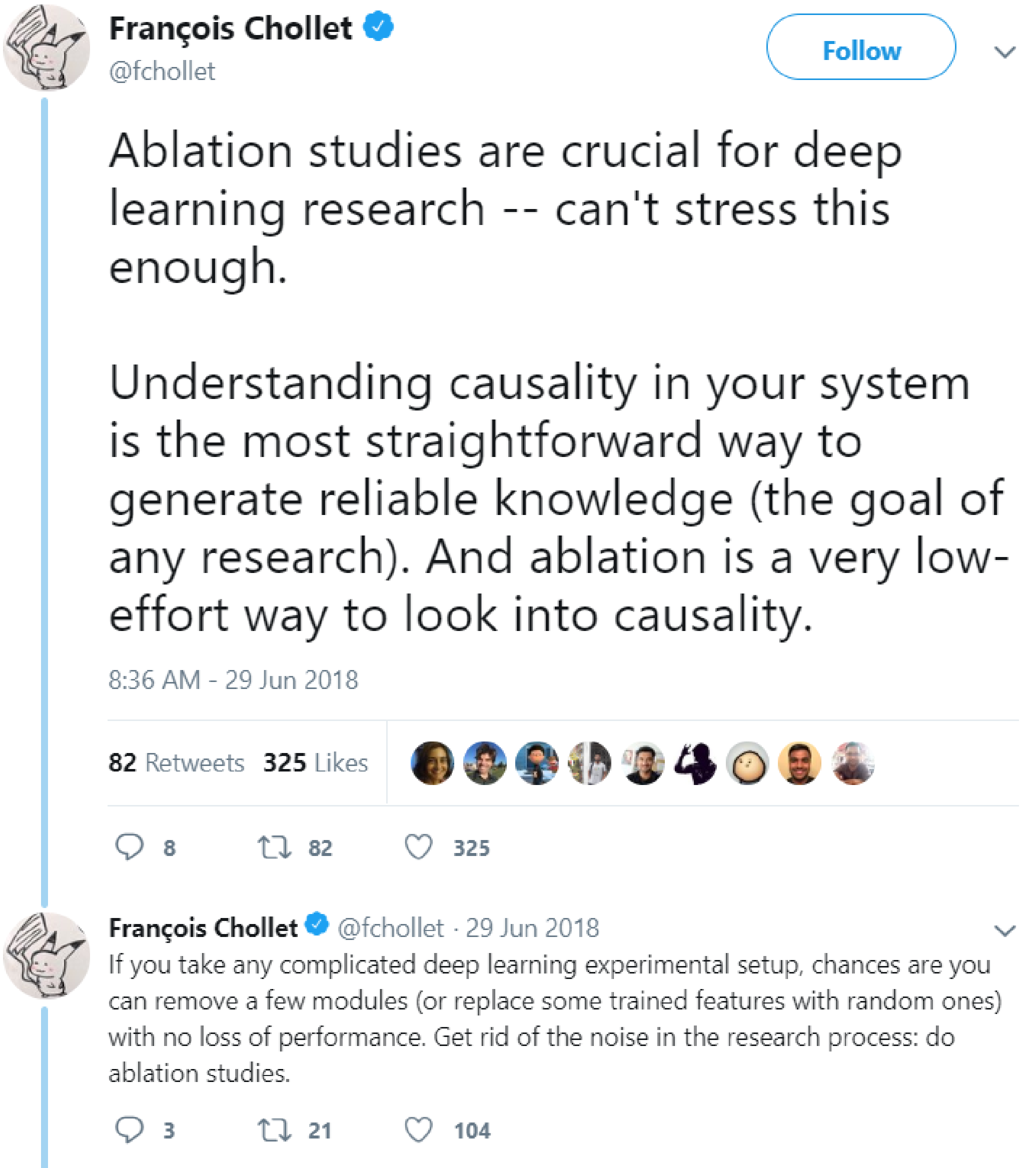
How much can we simplify the baseline model?

François Chollet. Author of Keras, the popular Deep learning library for TensorFlow.



Ablation experiment (I) – Reduce channels

```
(Conv2D(16, kernel_size=(3, 3), activation='relu', input_shape=(299, 299, 3)))
(MaxPooling2D(pool_size=(2, 2)))
(Conv2D(32, kernel_size=(3, 3), activation='relu'))
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(Dropout(0.5))
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```

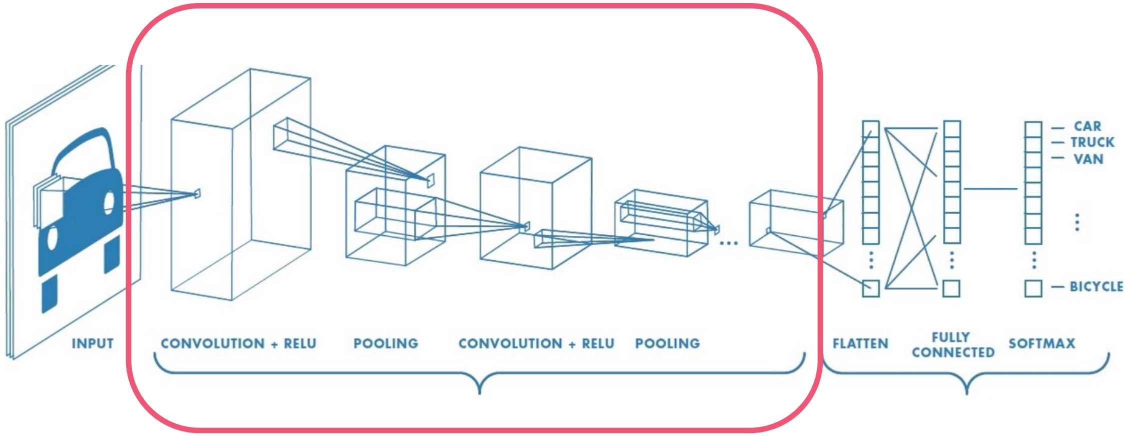

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Ablation experiment (I) – Reduce channels

Incremental channels factor = 2		
Layer	**Channels**	**# parameters**
Conv2D-1	16	448
Conv2D-2	32	4640
Conv2D-3	64	18496
Conv2D-4	128	73856
Conv2D-5	256	295168
	Total	**392608**

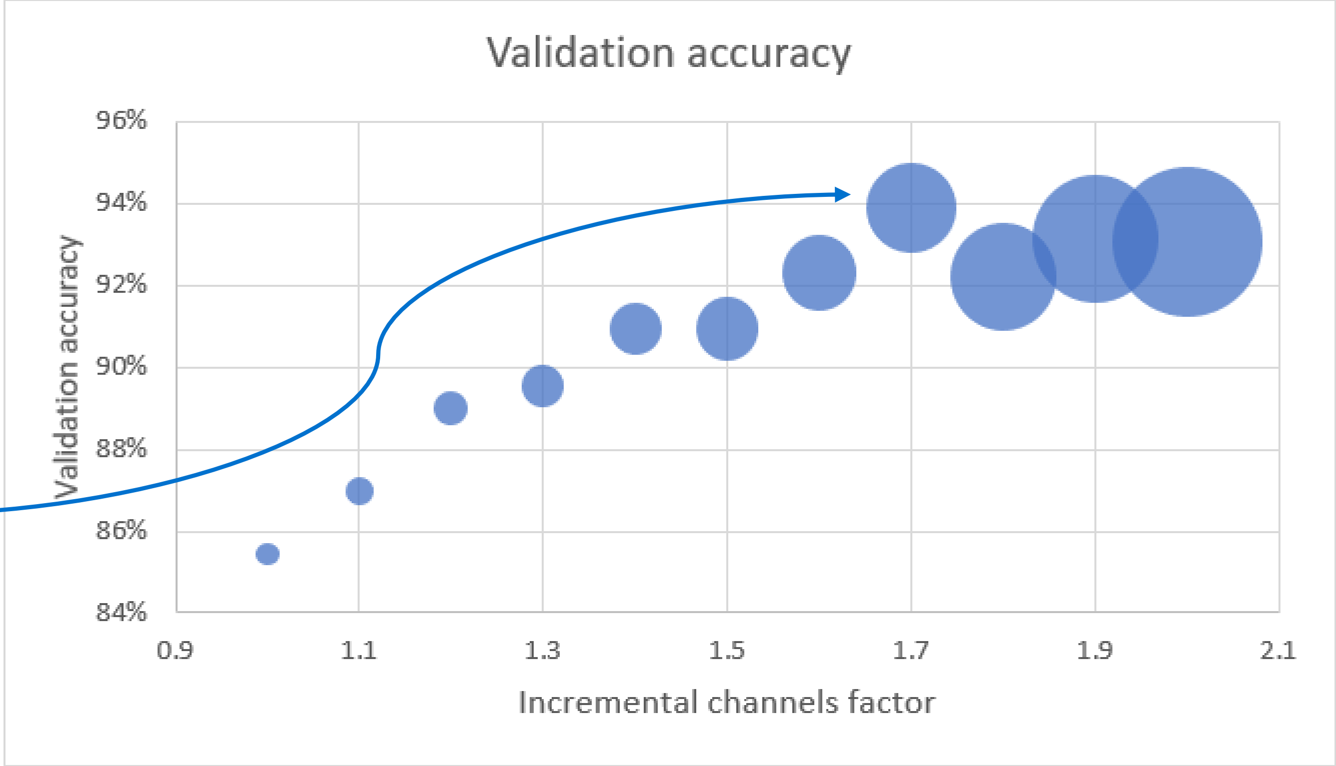
Incremental channels factor = 1.9		
Layer	**Channels**	**# parameters**
Conv2D-1	16	448
Conv2D-2	30	4408
Conv2D-3	58	15861
Conv2D-4	110	57159
Conv2D-5	209	206157
	Total	**284033**

...

Incremental channels factor = 1.1		
Layer	**Channels**	**# parameters**
Conv2D-1	16	448
Conv2D-2	18	2552
Conv2D-3	19	3086
Conv2D-4	21	3732
Conv2D-5	23	4513
	Total	**14331**

Ablation experiment (I) – Reduce channels

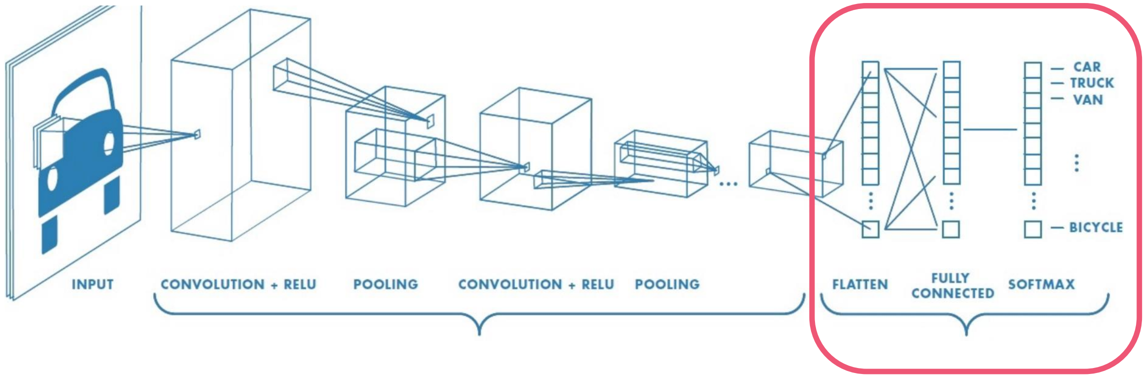
ICF	Total parameters	Validation accuracy
1	9728	85.44%
1.1	14331	86.98%
1.2	21286	89.01%
1.3	31646	89.56%
1.4	46834	90.95%
1.5	68737	90.93%
1.6	99815	92.30%
1.7	143226	93.89%
1.8	202965	92.22%
1.9	284033	93.13%
2	392608	93.06%



Size of the circles is indicative of the number of parameters.

Ablation experiment (II) – Reduce size of fully connected layers

```
(Conv2D(16, kernel_size=(3, 3), activation='relu’, input_shape=(299, 299, 3)))
(MaxPooling2D(pool_size=(2, 2)))
(Conv2D(27, kernel_size=(3, 3), activation='relu'))
(MaxPooling2D(pool_size=(2, 2)))
(Conv2D(46, kernel_size=(3, 3), activation='relu'))
(MaxPooling2D(pool_size=(2, 2)))
(Conv2D(79, kernel_size=(3, 3), activation='relu'))
(MaxPooling2D(pool_size=(2, 2)))
(Conv2D(134, kernel_size=(3, 3), activation='relu'))
(MaxPooling2D(pool_size=(2, 2)))
(Dropout(0.5))
(Flatten())
(Dense(48, activation='relu'))
(Dropout(0.5))
(Dense(24, activation='relu'))
(Dropout(0.5))
(Dense(3, activation='softmax'))
```



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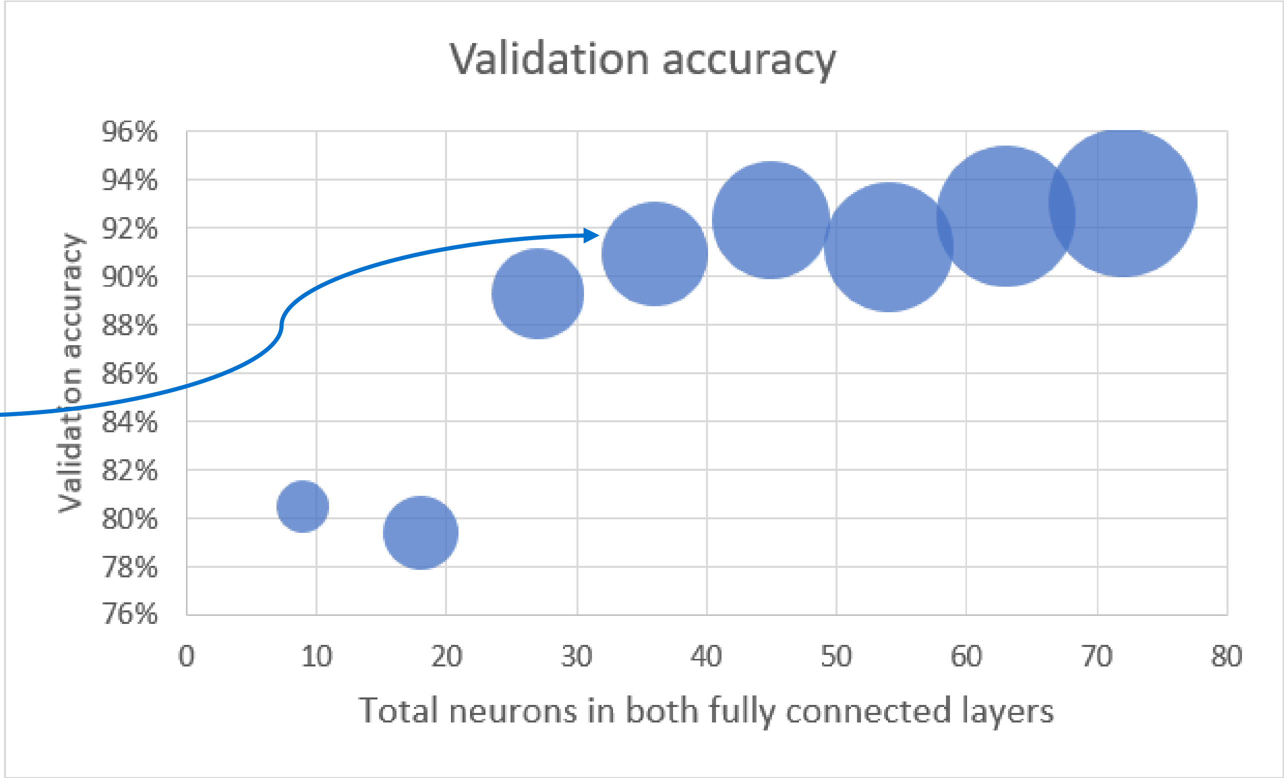
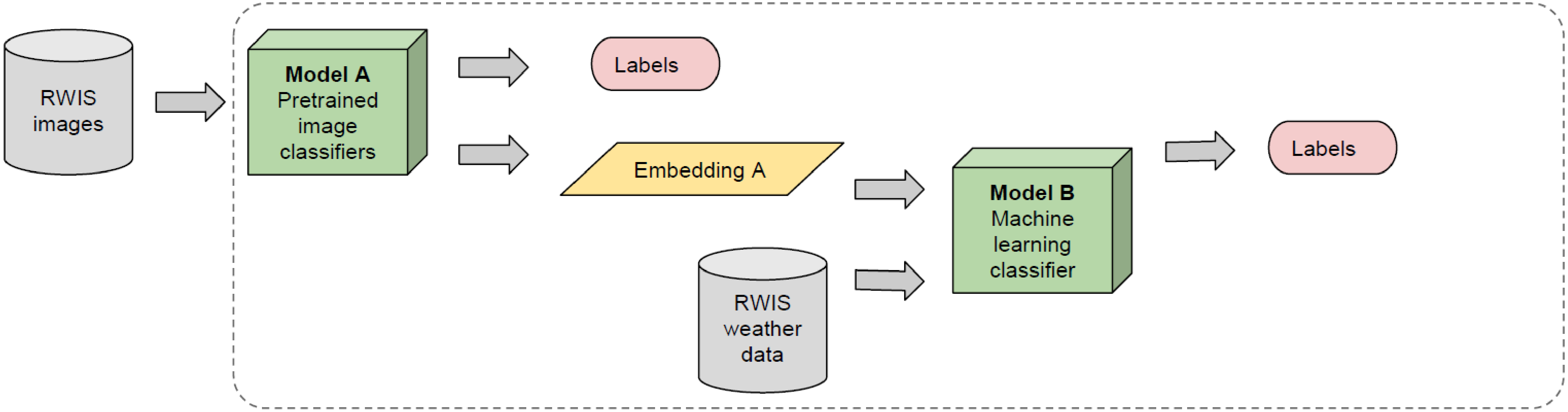
Ablation experiment (II) – Reduce size of fully connected layers

FC 1	FC 2	FC1+FC2	Total parameters	Validation accuracy
48	24	72	316467	93.06%
42	21	63	276783	92.50%
36	18	54	237135	91.23%
30	15	45	197523	92.38%
24	12	36	157947	90.95%
18	9	27	118407	89.29%
12	6	18	78903	79.40%
6	3	9	39435	80.48%

Size of the circles is indicative of the number of parameters.



Including Weather data



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Including Weather data

- 40 RWIS stations across Ontario
- 14.000 images in total
- 70.000 observations from five weather variables

- Air Temp (°C)
- Relative Humidity(%)
- Pressure (kPa)
- Wind Speed (km/h)

Image source

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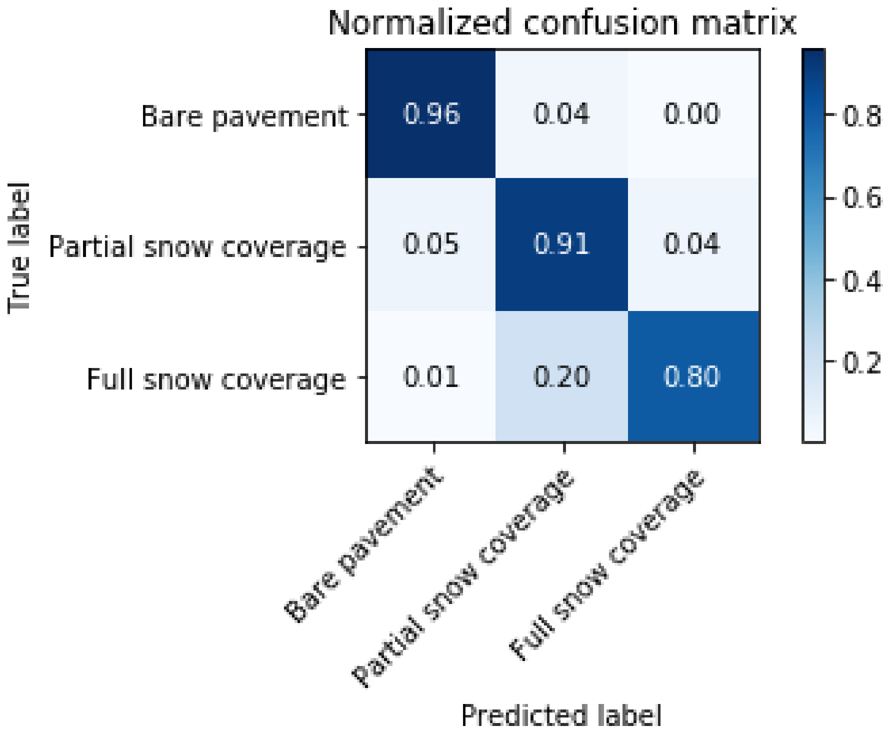
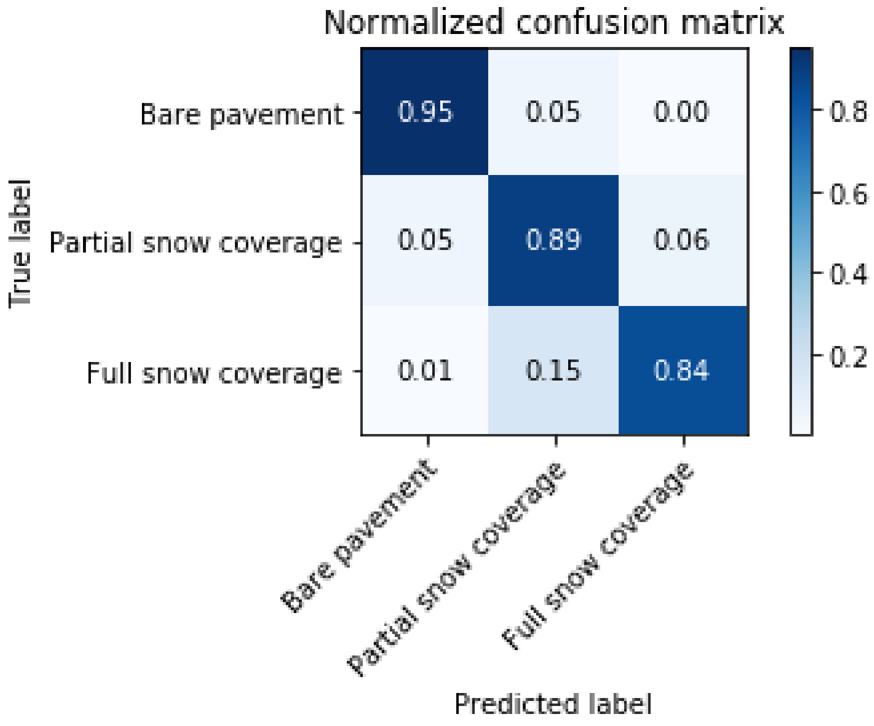
Confusion matrix over the test set – Naïve Bayes classifier

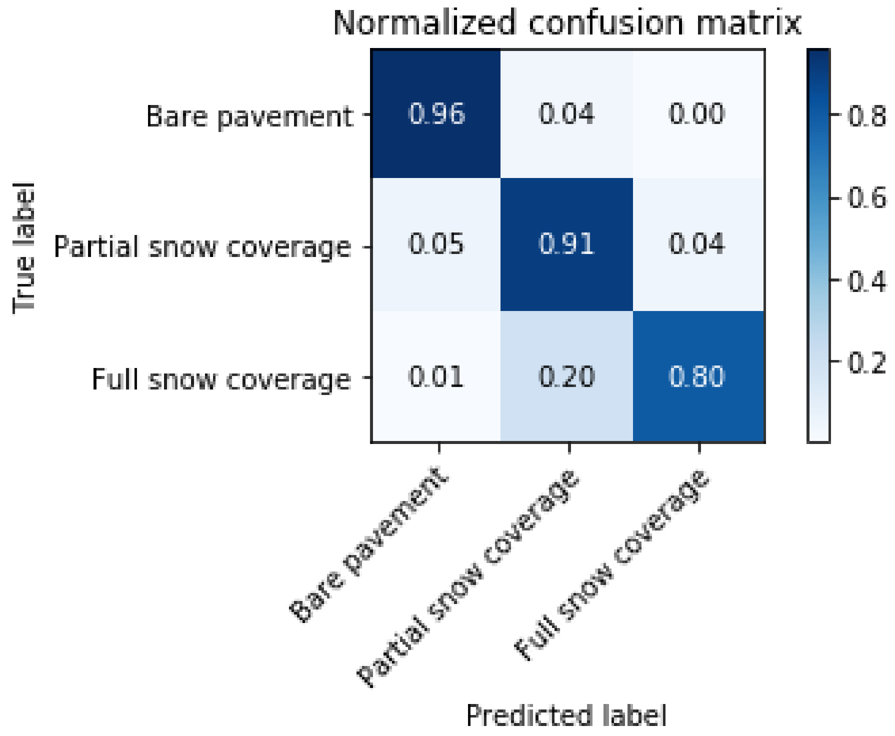


Compressed baseline

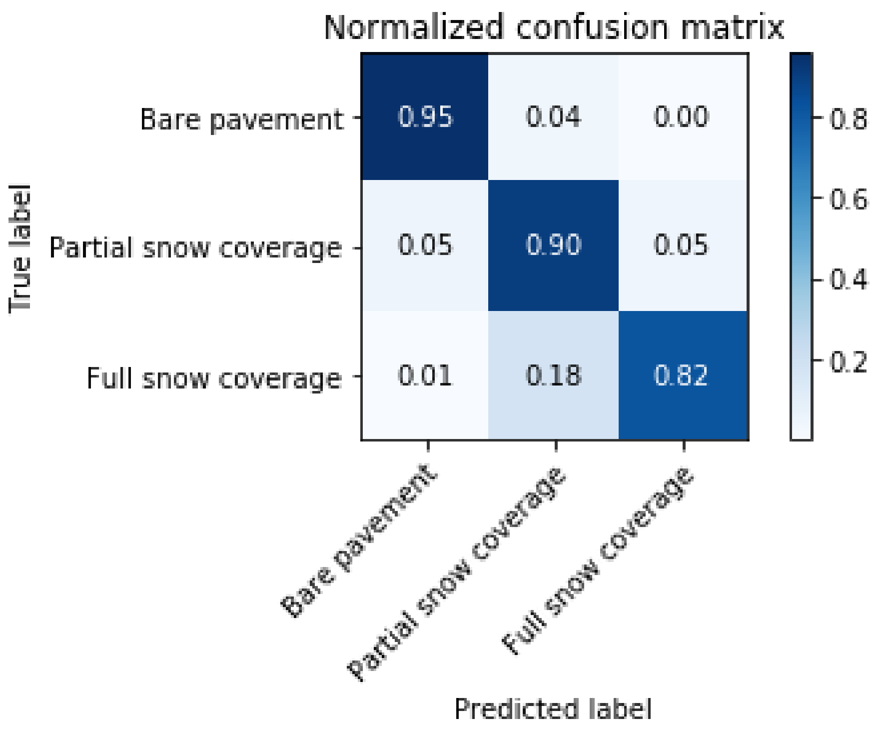


Compressed baseline + weather

Confusion matrix over the test set – Random Forest classifier



Compressed baseline



Compressed baseline + weather

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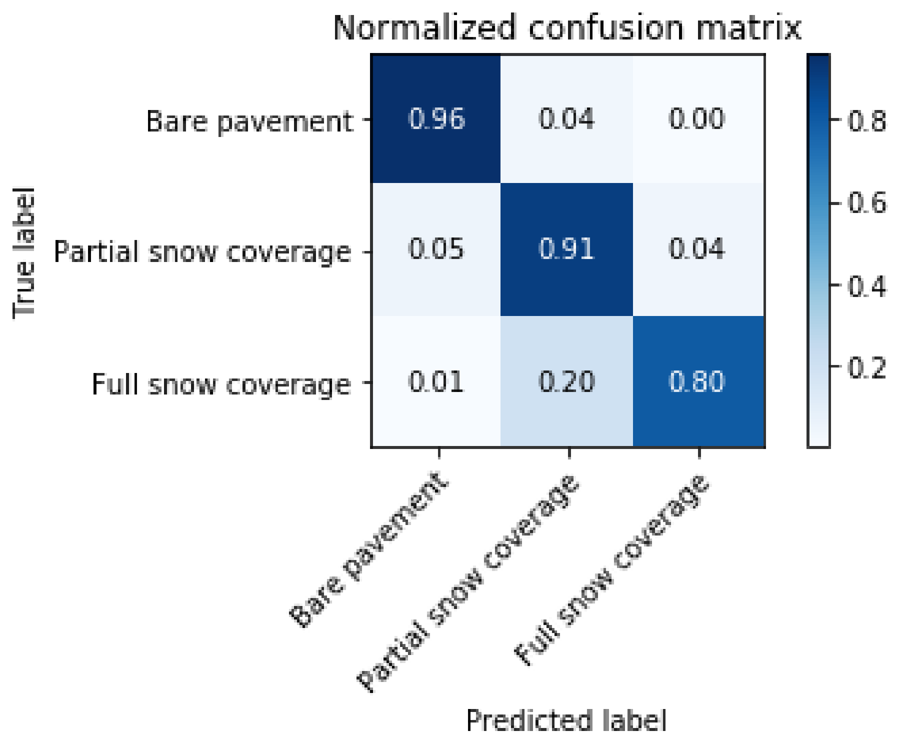
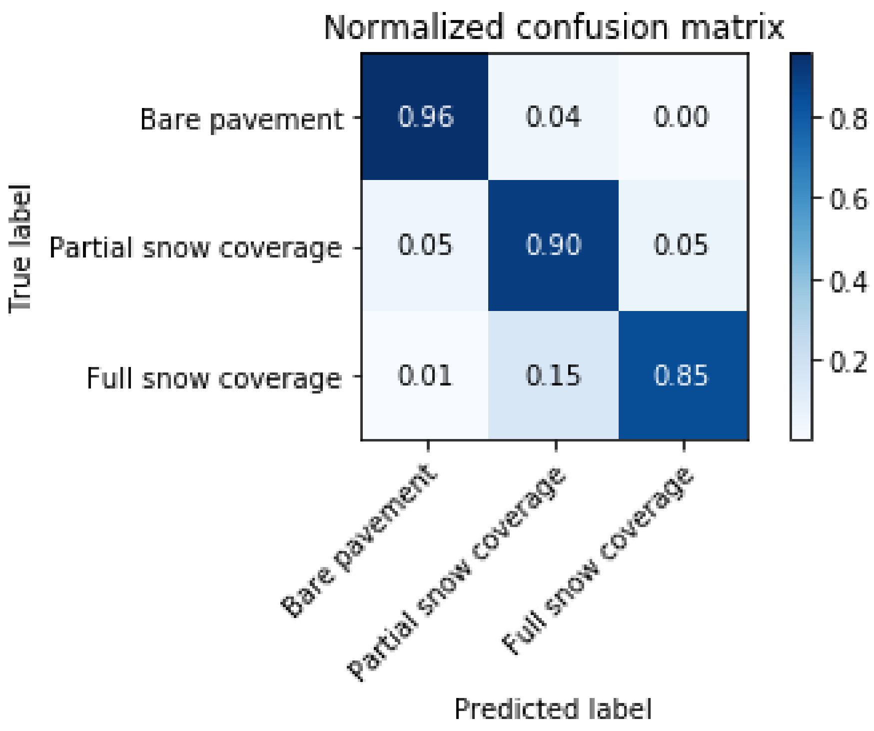
Confusion matrix over the test set – SVM classifier



Compressed baseline



Compressed baseline + weather

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Conclusions 4

Conclusions

- By adding all other MTO cameras as image data sources to the RWIS system, **six times** more cameras are available in Southern ON.

- Adding weather stations from Environment Canada to the RWIS system increases the number of weather stations by **1.7x**.

- The best experimental tradeoff between complexity and accuracy to interpolate weather variables is offered by the method Radial Basis Functions (RBF).

- For certain applications, a rather simple Deep Convolutional Neural Network (DCNN) model can perform better than heavy weight DCNN models.

- Using weather variables does not improve classification of Road Surface significantly.

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