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Article

WeatherNet: Recognising Weather and Visual Conditions from Street-Level Images Using Deep Residual Learning

Mohamed R. Ibrahim *, James Haworth and Tao Cheng

SpaceTimeLab, Department of Civil, Environmental and Geomatic Engineer, University College London (UCL) Gower Street, London WC1E 6BT, UK; j.haworth@ucl.ac.uk (J.H.); tao.cheng@ucl.ac.uk (T.C.)

* Correspondence: mohamed.ibrahim.17@ucl.ac.uk or mibrahim2006@me.com

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Outline

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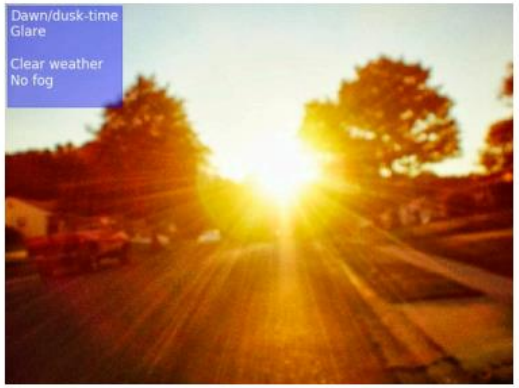
- Conclusions

Background and Objectives

- Extracting dynamic information of weather and visual conditions is meaningful for meteorology monitoring, smart city planning, autonomous drive-assistance, etc.
- Weather and visual conditions are often addressed individually
  - weather: snow, fog, rain, sunny, etc.
  - visual: dawn/dusk, day/night, glare or no glare, etc.
- This paper proposed a unified method – **WeatherNet** framework
  - 4 deep convolutional neural networks
  - from street-level images
  - no pre-defined constraints in processed images



(a) Dawn/dusk time with glare and clear weather

Figure 1. *Cont.*

(b) Day-time with snowy weather

(c) Dawn/dusk-time with glare and foggy weather

Comparison of Weather Classification Methods

Table 1. Comparison of approaches for weather classification.

Approach	Mathematical Models	Filtering-Based Models	Machine Learning Models	Deep Learning Models
Advantage	• Easily interpreted • Minimal data required	• Easily interpreted • Minimal data required	• Faster algorithms • Less complex than deep learning models	• Multi-labelling—transfer learning • High accuracy • Minimal pre-defined settings • Unrestricted image dataset • Easily implemented
Disadvantage	• Model fit for a specific task • User-defined settings • Less accurate	• Model fit for a specific task • User-defined settings • Depends of the pixel values of the image	• Model fit for a specific task • Requires data fusion for multiple sources • Require large dataset	• Computationally intensive for training • Difficult to interpret the model structure • Require large, labelled dataset

requires camera optics and viewing distances

less transferable to different weather and visual conditions

WeatherNet

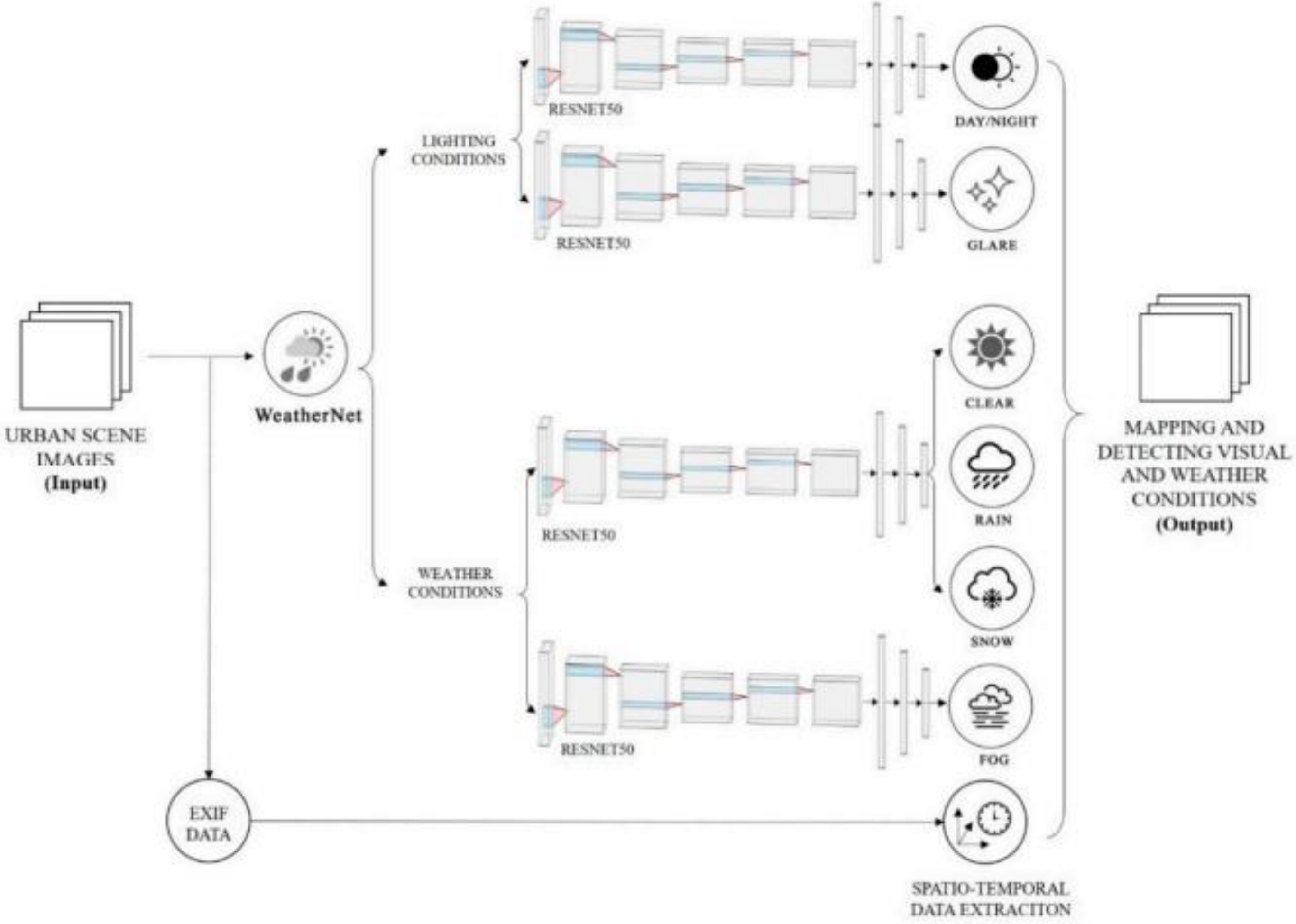


Figure 2. The framework of WeatherNet.

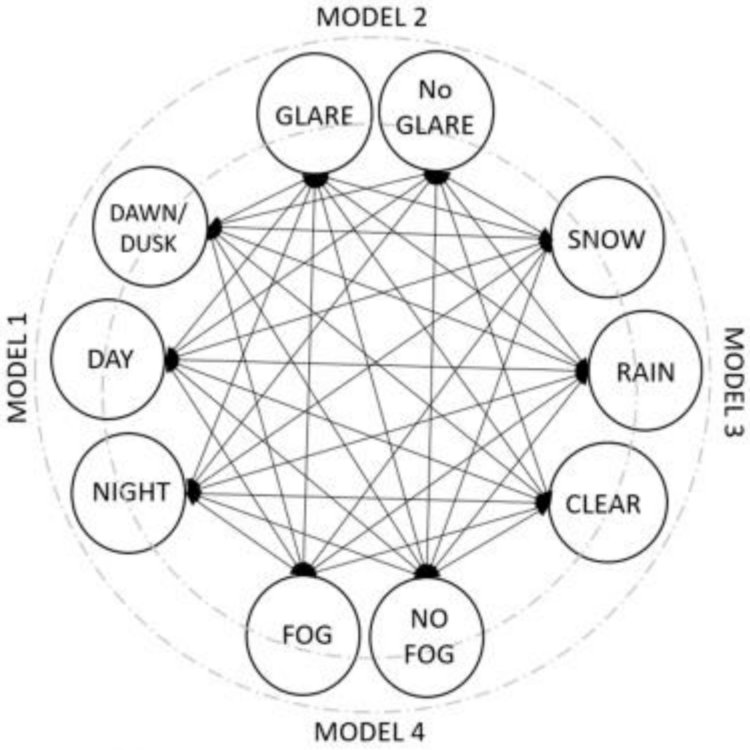


Figure 3. Exclusive vs. co-existing classification classes.

Images are resized to (224x224x3) and fed-forward to the ResNet via transfer learning (pre-trained on ImageNet database)

Dataset

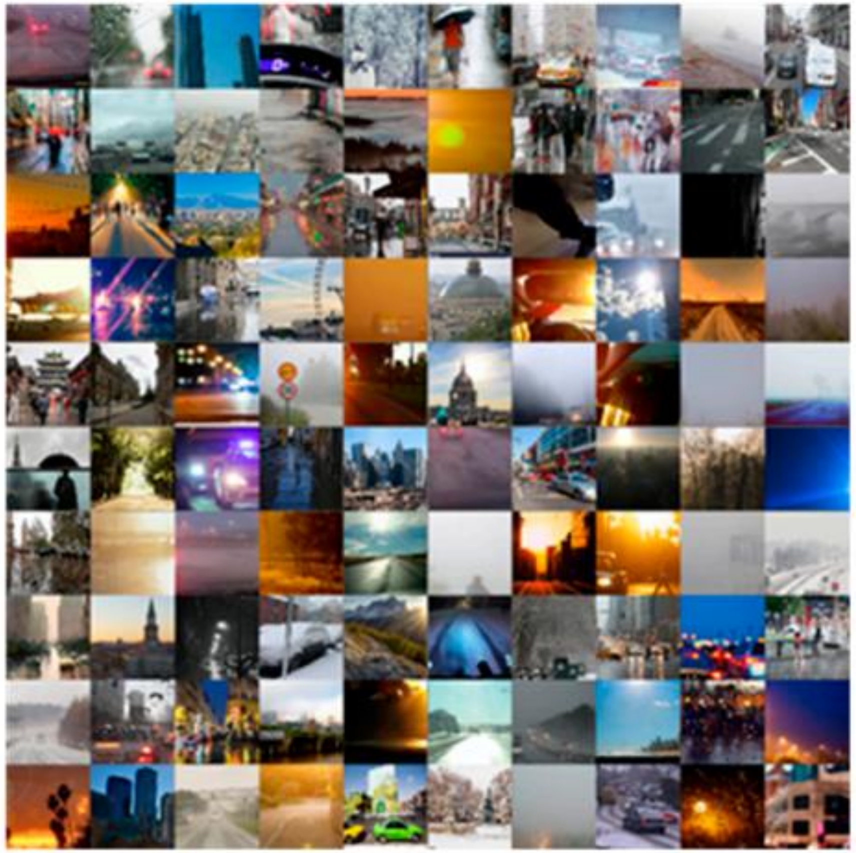


Figure 4. Samples of WeatherNet dataset.

Table 2. Sample size and categories of the datasets.

CNN Model	Dataset Classes	Sample Size
Model1—NightNet	Dawn/Dusk	1673
	Day	2584
	Night	1848
Model2—GlareNet	Glare	1159
	No glare	3549
Model3—PrecipitationNet	Clear	4017
	Rain	2343
	Snow	2347
Model4—FogNet	Fog	718
	No fog	3627

- Total 23865 collected manually from Google Images
- Manually labelled
- Split 80%-20%

Evaluation Metrics

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \quad (4)$$

$$Precision = TP/(TP + FP) \quad (5)$$

$$Recall = TP/(TP + FN) \quad (6)$$

$$False - positive\ rate = FP/(FP + TN) \quad (7)$$

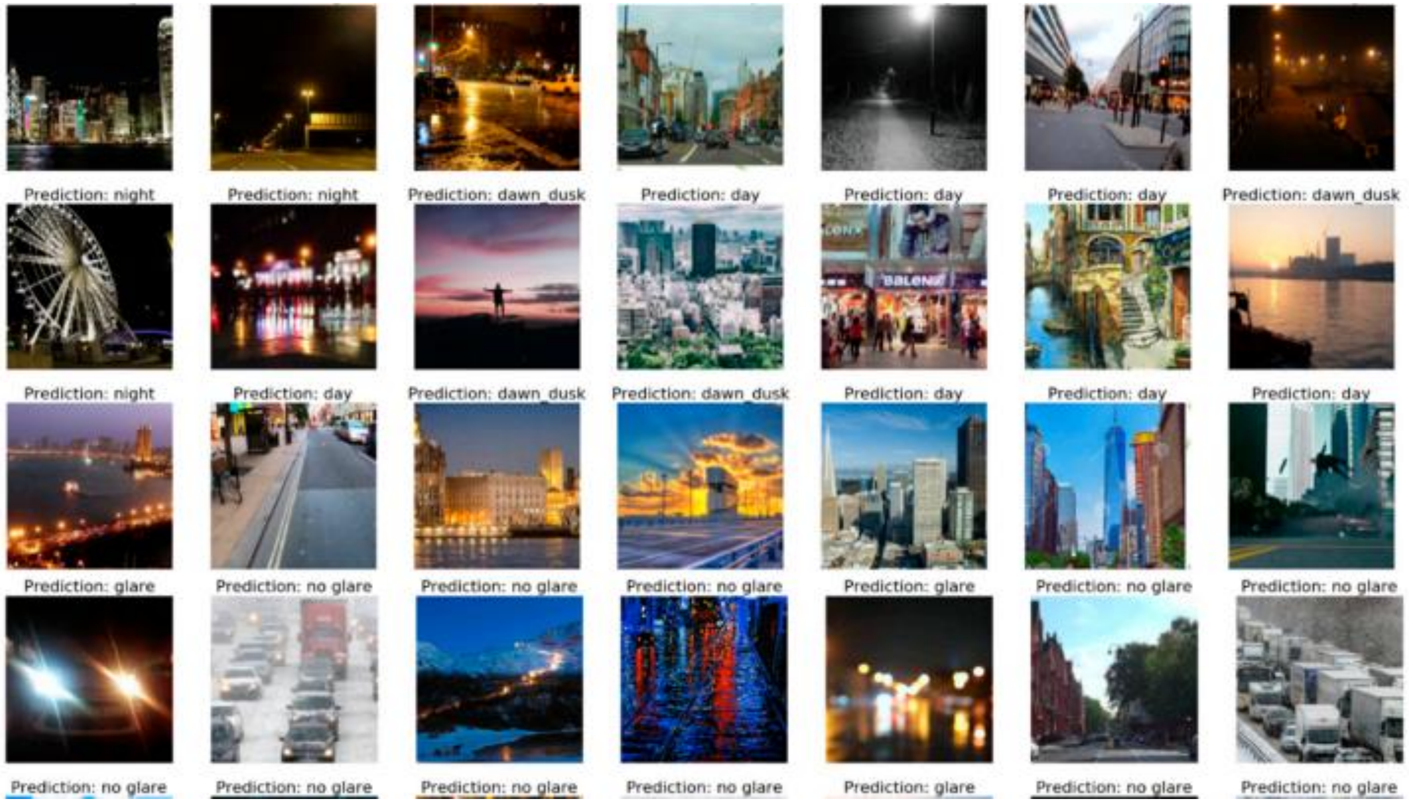
$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (8)$$

Results

Table 3. Diagnoses of the Convolutional Neural Network models for the test sets.

CNN Model	Loss (Cross Entropy)	Accuracy (%)	Precision [a]	Recall/True-Positive Rate [a]	False-Positive Rate [a]	F1-Score
Model1—NightNet	0.098	91.6	0.885	0.825	0.045	0.854
Model2—GlareNet	0.040	94.8	0.883	0.895	0.035	0.889
Model3—PrecipitationNet [b]	0.077	93.2	0.959	0.932	0.068	0.947
Model4—FogNet	0.037	95.6	0.862	0.829	0.022	0.845

[a] The metrics are evaluated for the referenced class—indexed zero—for each model. [b] This model contains three classes, in which the false-positive rate is shared with the classes prior to the referenced class.



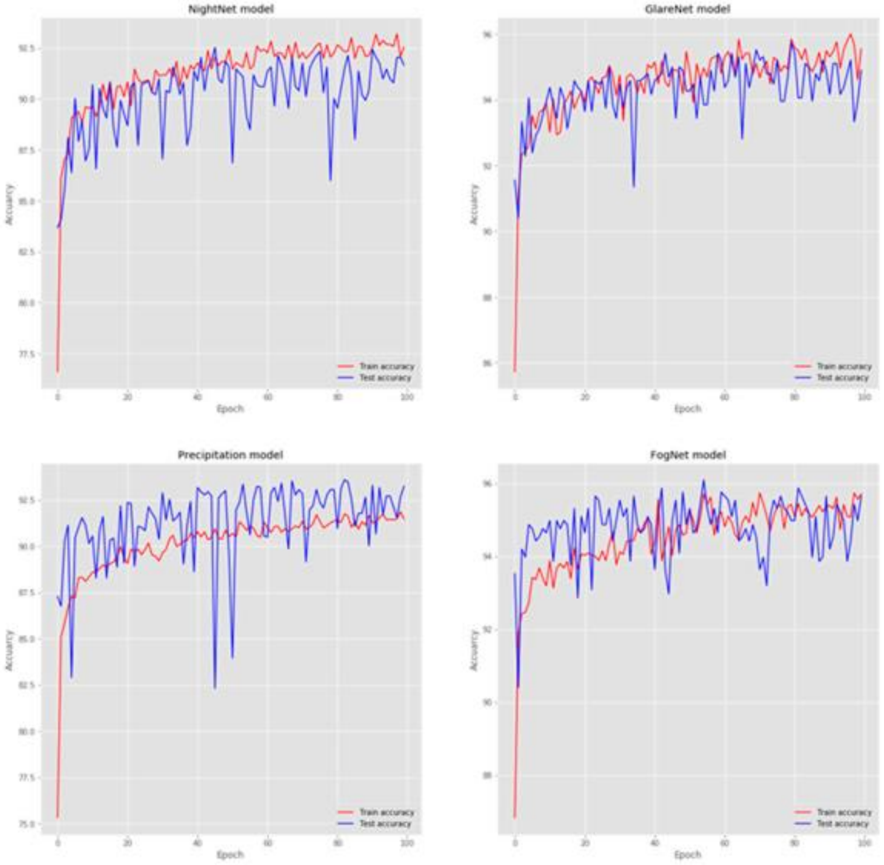


Figure 5. The training and testing accuracies per training cycle for each CNN model.

Comparison to other models

Table 4. Evaluations of the state-of-the-art models based on model types, scope, and classification labels.

Methods		Night-Time Detection (Classes)	Glare Detection	Fog Detection	Weather Detection (Classes)	Overall Score
[17]	Regions of interest—Histograms	-	-	-	x (clear, light rain, heavy rain)	0.85
[40]	Support Vector Regressor	-	-	-	x (clear, partly cloudy, mostly cloudy, cloudy)	NA
[38]	Random Forest Classifier	-	-	x	x (Sunny, cloudy, rainy, snowy)	0.70
[27]	CNN model	-	-	-	x (Sunny, cloudy)	0.91
[28]	Different types of CNN models	-	-	x	x (snowy, rainy)	0.80
[41]	SAID ENSEMBLE METHOD	-	-	-	x (sunny, cloudy, rainy)	0.86
[29]	CNN-LSTM	-	-	x	x (sunny, cloudy, rainy, snowy)	0.91
WeatherNet	**Multiple Residual deep models**	**x (Dawn/dusk, day, night)**	**x**	**x**	**x (Clear, rain, snow)**	**0.93**

Table 5. Evaluations of the WeatherNet framework on other open-sourced datasets.

Open-Sourced Benchmark Datasets	Total Images		Labels	Method	Testing Scope	Original Method Score	WeatherNet Score
Multi-class Weather Dataset for Image Classification	[41]	1125	Cloudy, sunshine, rain, sunset	SAID ENSEMBLE METHOD II	Rain detection	Accuracy: 95.20%	**Accuracy: 97.69%**
Multi-label weather dataset (test-set)	[29]	2000	(Sunny, cloudy, rainy, snowy, foggy)	CNN-Att-ConvLSTM	Sunny/clear detection Fog detection Rain detection Snow detection	(Precision/Recall): 0.838/0.843 (Precision/Recall): 0.856/0.861 (Precision/Recall): 0.856/0.758 (Precision/Recall): 0.894/0.938	**(Precision/Recall): 0.924/0.827** **(Precision/Recall): 0.833/0.940** **(Precision/Recall): 0.958/0.651** **(Precision/Recall): 0.789/1**

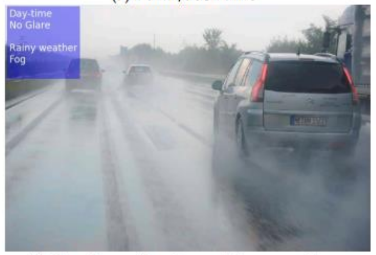
Innovation and Limitations

- tackling various weather and visual conditions, which has never been tackled together in any previous deep learning and computer vision research
- does not require any pre-defined constraints, such as applying filters, defining camera angles, or defining an action area to the processed images

- hyperparameter optimization
- using a sequential images or video streams
- street-level images from Google are not reflecting real-life situations

(a) Dawn/dusk time

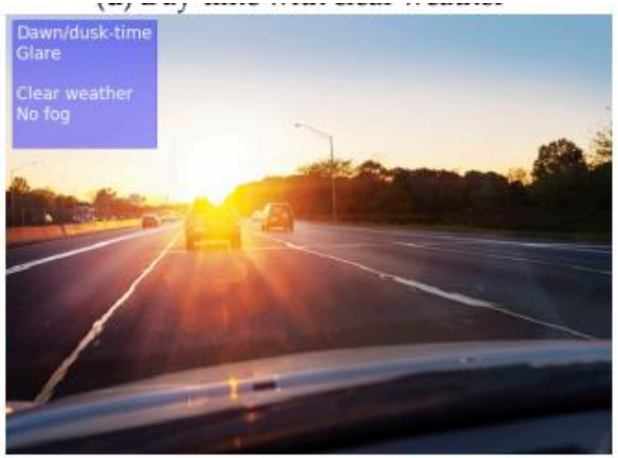
(b) Night-time with snowy weather



(c) Day-time with rainy and foggy weather

(d) Day-time with clear weather

(e) Night-time with glare



(f) Dawn/dusk-time with glare

Figure 7. Samples of the testing images using the WeatherNet framework.

Conclusions

- Proposed a unified method to tackle weather and visual conditions based on street-level images
  - WeatherNet
    - 4 ResNet model
    - Images from Google Images
    - no pre-defined constraints on images
- Comparable or better performance compared with other models
- Computational-intensive and dataset is not representative

Back Up