Developing and Evaluating an Integrated Machine Learning Approach to Estimating Near Real-Time Local Level Concentrations of Outdoor Ultrafine Particles using Street-Level Images and City Sounds

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A. Capture Images and Spectrograms	B. Measure UFPs	Introduction Traffic-related air pollution and noise are known to have adverse
Figure 1. Platform installation Figure 2. Platform components	and Noise	impacts on human health
	igure 5. UFP monitor	 Most exposure modelling studies focus on long-term exposures, there is a gap in near real-time local level exposures <u>Study Aim</u>: Develop a new platform that captures street-level images and spectrograms to generate near real-time predictions of outdoor ultrafine particle (UFPs; particulate matter < 100 nm) concentrations and noise (dB(A)).

partector2





Figure 4. Ten-second spectrogram



C. Train Separate Deep Convolutional

Summary

<u>A. Platform:</u>

 Solar powered device (Figure 1) mounted on city street pole
 Raspberry Pi computer and modem (Figure 2) transmitted streetlevel images (Figure 3) and 10-second spectrograms (Figure 4)
 <u>B. Exposures:</u>



•UFP number concentrations and UFP size measured every 1 second using Naneos Partector 2 (Figure 5)

•Noise measured every 1 second using Convergence Instruments NSRT Mk4 (Figure 6)

Monitoring Campaign:

Images, spectrograms, UFPs, and noise were measured at 11 roadside locations across Montreal, Canada during 2021-2022
Approximately 300,000 samples were collected

Data Preparation:

•A 10-second moving average and log transformations were applied to UFP concentration, UFP size, and noise

•Data randomly split into train, validate, and test sets (80-10-10)

C. Convolutional Neural Network (CNN) Model Training:

 Separate models were trained on images and spectrograms to train UFP number concentration, UFP size, and noise (Table 1)
 Xception or ResNet architectures were used

<u>D. Temporal Adjustment:</u>

•CNN Predictions were combined with regional weather and fine particulate matter concentrations (PM_{2.5}) using XGBoost models in the train and validate sets

Neural Network (CNN) Models

Table 2. CNN models



Model #	Predictor	Predicted Exposure
1	Images ~	log(UFP Concentration)
2	Images ~	log(UFP Size)
3	Images ~	log(Noise)
4	Spectrograms ~	log(UFP Concentration)
5	Spectrograms ~	log(UFP Size)
6	Spectrograms ~	log(Noise)

D. Combine CNN Predictions and Regional Atmospheric Conditions in XGBoost Models

E. Model Performance in Test Set:

•CNN predictions using images and spectrograms were used to generate XGBoost model predictions in the test set
•Models explained 92.6% of the variance in the observed UFP number concentrations (Figure 7 and Table 2)
•Models explained 91.3% of the variance in the observed noise (Figure 8 and Table 2)

Impact

•New platform offers an efficient means of predicting local-level noise and UFP concentrations in near real-time

 Could be used to support future epidemiological analyses or applied in occupational environments where noise and vehicle emissions are a concern

 $log(UFP\ Concentration) \sim xgboost(UFP\ Conc_{CNN\ \#1}, UFP\ Conc_{CNN\ \#4}, UFP\ Size_{CNN\ \#2}, UFP\ Size_{CNN\ \#5}, Temp, Wind\ Speed, PM_{2.5})$

 $log(Noise) \sim xgboost(Noise_{CNN \#3}, Noise_{CNN \#6}, UFP Size_{CNN \#2}, UFP Size_{CNN \#5}, Temp, Wind Speed, PM_{2,5})$

E. Evaluate Model Performance in Test Set

