Overview of MediaEval 2022 Urban Air: Urban Life and Air Pollution

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Abstract
Air pollution and urban life mutually influence each other, posing a challenge for urban management. Monitoring air pollution and urban activities through systems like air pollution stations and CCTV has led to the development of prediction methods and applications. However, limited access to data and narrow datasets with ideal conditions hinder research efforts. To address this, we introduce the UrbanAir task, which provides a streaming dataset from CCTV and air stations in Dalat City, Vietnam. This task focuses on multimodal and crossmodal prediction of air pollution, even in the absence of data from specific stations. It targets researchers in fields such as multimedia information retrieval, machine learning, AI, data science, urban management, and environmental science, among others.

1. Introduction

Air pollution poses grave threats to human health due to factors such as industrial development, climate change, agrochemical use, and urbanization. In the EU alone, at least 238,000 premature deaths were reported in 2020 due to PM2.5 pollution [1]. Fuel combustion in various sectors, including residential, commercial, institutional, and transportation, was identified as a significant source of particulate matter pollution. Road transport, agriculture, and industry were the primary sources of increasing nitrogen oxide (NO2) emissions, resulting in 49,000 deaths in the EU. Exposure to ozone also contributed to 24,000 premature deaths in the EU.

Despite these dangers, 99% of the global population lived in areas where WHO's air quality guidelines were not met in 2019 [2]. In 2019, around four million people died due to fine particulate outdoor air pollution, with highest death rates observed in East Asia and Central Europe.

Hence, there is an urgent need for robust models to predict air pollution and uncover correlations with human activities, especially in urban settings. This task aims to develop a novel framework to uncover localized correlations between traffic factors, weather conditions, and air pollution, with the goal of enhancing Air Quality Index (AQI) prediction accuracy and deepening understanding of the mutual impact between urban life and air pollution.

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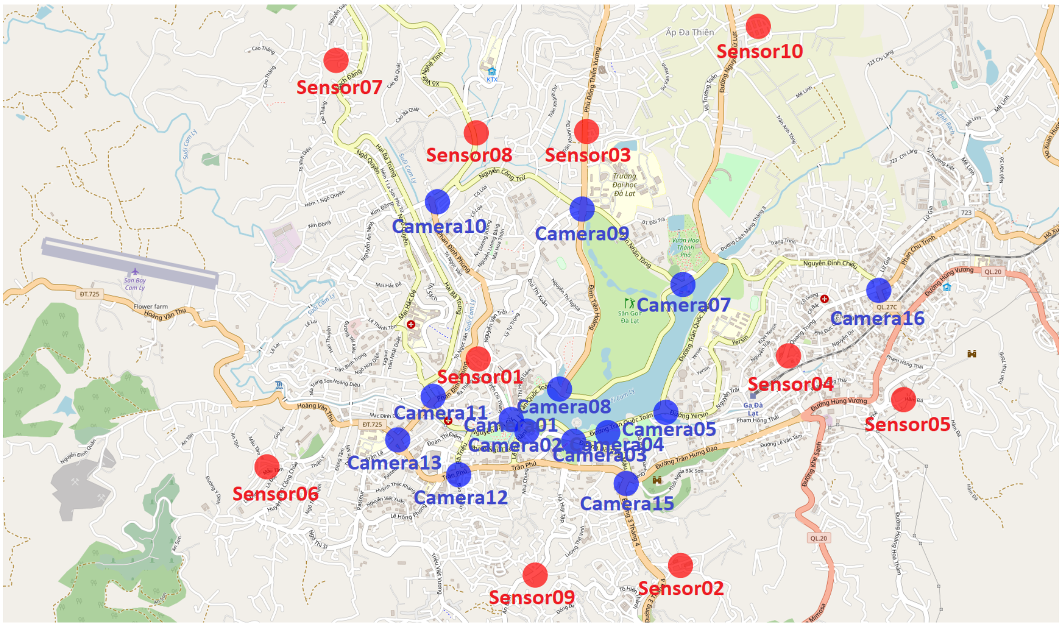

Figure 1: Air pollution, weather stations, and CCTV network distribute in Dalat city, Vietnam.

2. Data Description

The data utilized in this study is directly obtained from various sources, including air pollution, weather, and CCTV stations that are strategically installed across Dalat City, Vietnam. Specifically, there are ten air pollution stations (referred to as sensor01-10), with three of them attached to weather stations (sensor01, sensor02, sensor03), as depicted in Figure 1. In addition, there are fourteen CCTV cameras that provide traffic-related data. For the purpose of this study, the terms "environmental data" and "traffic data" are used interchangeably with air pollution/weather data and CCTV data, respectively, as provided by the air pollution and weather stations, as well as the CCTV networks.

At each air pollution station, sensory data is collected and recorded, encompassing parameters such as Temperature, Humidity, PM1.0, PM2.5, PM10, CO, NO2, SO2, O3, and UV. Similarly, the weather stations capture data on WindSpeed, WindGust, Direction, and Rainfall. All stations are identified by unique codes, including SensorID, SensorCode, SensorName, Latitude, Longitude, and Altitude, which provide their specific location information. Data at these stations are recorded at frequent intervals based on Date and Time.

On the other hand, each CCTV camera is identified by distinct codes, including CameraID, CameraCode, CameraName, Latitude, and Longitude, which denote their location information. Data from these cameras, including Date, Time, and Image, can be accessed by individuals. Notably, only images are stored instead of videos to conserve storage space.

All the collected data from the air pollution, weather, and CCTV stations are continuously streamed and made accessible to task participants through the project's website and the *ftp* protocol, granting convenient access for research and analysis purposes.

3. Task Description

We have designed two subtasks for participants in order to leverage multimodal and crossmodal prediction models for air pollution and traffic prediction. Subtask 1 challenges participants to predict air pollution levels using only environmental data, while subtask 2 requires the use of traffic data exclusively. However, subtask 2 allows for training a prediction model using both environmental and traffic data, but only traffic data can be used for predicting air pollution. Subtask 1 requires predicting both the exact concentration value and AQI (Air Quality Index) level for each pollutant, whereas subtask 2 only requires AQI levels.

Subtask 1 presents a traditional prediction problem where predicted results are influenced by historical data. However, in this challenge, participants are encouraged to use data from one or a group of stations to predict data from other stations. The real challenge here lies in dealing with live-dead circumstances, where there is no guarantee that a particular station will operate consistently for an extended period of time. Relying solely on data from one sensor may result in poor model performance if that sensor is offline for some time, or if it produces inaccurate data due to unexpected local effects caused by human activities or natural factors. Furthermore, this subtask aims to develop robust models that can predict air pollution in areas without dedicated monitoring stations by utilizing data from neighboring stations.

The original idea behind subtask 2 is to use images to estimate AQI levels concurrently [3]. For example, participants can utilize images, either current or historical, captured by one camera or a group of cameras to estimate AQI levels at nearby locations. Scenarios for this subtask could include using images from smartphones to estimate AQI levels based on images captured around a location, or utilizing CCTV images to estimate AQI levels in the surrounding areas.

Participants are required to make predictions for air pollution levels at three different moments of the day (8 am-9 am, 11 am-12 pm, and 5 pm-6 pm) on days D+1, D+5, and D+7, where D represents the day of submitting the predicted results.

4. Quest for Insight

In addition to the challenges outlined in the subtasks, there are several research questions associated with this challenge that participants can explore to move beyond a mere focus on evaluation metrics:

- Which factors from weather, air pollution, and CCTV data contribute to the air pollution prediction model?
- When building the correlation hypothesis between traffic, weather, and air pollution, what is the difference and similarity between people's experience and the model's knowledge?

This is the first instance of an open dataset being made available to the public, encompassing real-world challenges and unforeseen effects that have not been present in previous in-lab datasets. However, this dataset also serves as a valuable source of rich information that can offer valuable insights into addressing urban air pollution and associated life challenges. Many extraneous factors, such as the influx of tourists during weekends or festival events, the unique weather patterns, and the mountain-valley geography of Dalat city, can significantly influence air pollution levels and city dynamics. Participants are encouraged to explore and leverage external information beyond the dataset to enhance their models and uncover novel findings. Additionally, these factors represent only the tip of the iceberg, and participants are encouraged to dig deeper and uncover hidden gems in their quest for solutions.

5. Ground Truth and Evaluation

One of the unique aspects of this task is that participants have the opportunity to self-evaluate their predicted results using incoming or recorded data from the system as ground truth. For example, a prediction model can forecast the air pollution levels for days D+1, D+5, and D+7 on day D. When those days arrive, the predicted results can be compared against the actual air pollution values. Therefore, there is no predefined ground truth for evaluation, as the data from the sensors on the day of prediction may contain noise, outliers, or even be missing due to sensor shutdowns.

For evaluation, we utilize the incoming data to assess participants' results. The Mean Absolute Error (MAE) and Mean Squared Error (MSE) are used to evaluate the accuracy of prediction models for air pollutant values, while the F1-score is used for evaluating the accuracy of AQI levels, which are calculated based on the instructions provided in [4]. The AQI levels are divided into seven categories, namely Good, Moderate, Unhealthy for Sensitive Groups, Unhealthy, Very Unhealthy, Hazardous, and Extreme Hazardous. Participants are required to predict the values and AQI levels for six air pollutants, namely PM2.5, PM10, CO, NO2, SO2, and O3.

The task necessitates participants to submit their predicted results (for both subtasks) for days D+1, D+5, and D+7, with the submission format communicated to all participants via email.

6. Discussion and Outlook

Numerous methods have been proposed in the literature for air pollution prediction, utilizing various data sources such as air pollution stations [5], mobile air pollution devices [6], lifelog cameras [7], and satellites [8]. However, these methods often rely solely on datasets provided by third parties or collected by themselves, which have limitations such as being offline, in-lab, and incomplete, and may not capture the actual unexpected errors that occur in reality. In contrast, the task presented in this paper provides a streaming dataset that covers a wide range of scenarios, making it more challenging for participants to develop effective solutions that are applicable to real-world situations.

As the organizers of this task, we believe it can pave the way for a new direction in air pollution prediction research. Instead of solely relying on historical data from one sensor to predict its own values, we encourage participants to explore the use of subsets of sensors to predict values of other sensors or to incorporate data from different locations with unique characteristics. This approach may enable better detection of outliers and sudden changes in air pollution with higher accuracy. Furthermore, understanding the mutual impact of urban life and air pollution can lead to the development of explainable AI models for air pollution prediction, which can support improved urban management and healthcare services.

By leveraging additional data from local sources and considering the interplay between urban life and air pollution, we believe that this task can contribute to the advancement of air pollution prediction research and foster the development of innovative approaches that are better aligned with real-world scenarios.

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ASEAN-IVO [9] sponsors the air pollution and weather stations installed in Dalat city, Vietnam. It is the result of the international project, namely "Reusable, Shareable, and Transferable Smart Data Platform for Collaborative Development of Data-Driven Smart City" [10], conducted by partners from Japan, Vietnam, Singapore, Brunei, and the Philippines from 2020 to 2022. Dalat University, Vietnam, and LOC GOLD Technology MTV Ltd. Co, Vietnam, handle and maintain it. The CCTV system is sponsored by local citizens and handled by the police force of Dalat City, Vietnam.

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