RISE Video Dataset: Recognizing Industrial Smoke Emissions

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Figure 1: Samples in our dataset and the deployed camera system for monitoring industrial emissions at various sites.

ABSTRACT
Industrial smoke emissions pose a significant concern to human health. Prior works have shown that using Computer Vision (CV) techniques to identify smoke as visual evidence can influence the attitude of regulators and empower citizens in pursuing environmental justice. However, existing datasets do not have sufficient quality nor quantity for training robust CV models to support air quality advocacy. We introduce RISE, the first large-scale video dataset for Recognizing Industrial Smoke Emissions. We adopt the citizen science approach to collaborate with local community members in annotating whether a video clip has smoke emissions. Our dataset contains 12,567 clips with 19 distinct views from cameras on three sites that monitored three different industrial facilities. The clips are from 30 days that spans four seasons in two years in the daytime. We run experiments using deep neural networks developed for video action recognition to establish a performance baseline and reveal the challenges for smoke recognition. Our data analysis also shows opportunities for integrating citizen scientists and crowd workers into the application of Artificial Intelligence for social good.

KEYWORDS
Dataset, community citizen science, computer vision, air pollution, smoke recognition, human-computer interaction, sustainability, AI for social good, community empowerment

1 INTRODUCTION
Air pollution has been associated with adverse impacts on human health, including respiratory and cardiovascular diseases [13, 28, 41]. According to the United States Environmental Protection Agency (US EPA), hazardous air pollutants (e.g., smoke) emitted from industrial sources pose a significant concern [4]. Currently, citizens who wish to advocate for better air quality rely on a manual approach developed by the US EPA to determine if smoke emissions violate the issued permit to the facility [3]. This manual approach involves going into the field and taking multiple measurements, which is time-consuming and laborious. Prior works have shown that using Computer Vision to identify industrial smoke emissions automatically as visual evidence can empower citizens in pursuing environmental justice and influence the attitude of regulators [21, 22]. This type of data-driven evidence, especially when integrated with community narratives, is essential for citizens to make sense of local environmental issues and take community action [21, 39].

However, it is expensive and challenging to collect large-scale images or videos of real-world industrial smoke emissions, which are required to develop a practical smoke recognition model. Recent state-of-the-art models, deep neural networks, are typically data-hungry. Training these networks with insufficient data may lead to overfitting and raise concerns for application, such as high false alarm rates. Table 1 lists all the current datasets for smoke recognition, in which we count the number of videos and frames (using the ffprobe command in FFmpeg [1]) based on the data that are publicly available.\textsuperscript{1} Compared to datasets for object and action recognition, such as ImageNet [45] and Kinetics [29], existing datasets for smoke recognition are relatively small. Despite several successes in the prior works of using deep learning for smoke detection [5, 15, 24, 33, 38, 55–60, 63], these models were trained and evaluated on relative small video or image datasets (Table 1). In response to data sparsity, some prior works attempted to generate artificial smoke images, where smoke emissions with transparent background were synthesized with various scenes [55, 61, 63]. But such synthetic data cannot capture the rich behavior and appearance of smoke under real-world conditions, such as weather.

\textsuperscript{1} Some datasets treat steam as smoke, and we count the number of smoke frames within these datasets only based on the videos that do not involve steam. Moreover, some datasets contain videos for fire detection, and we did not count them in this table since fire detection is not our focus in this research.
where the smoke emissions frequently occur. Finally, these clips (6 am to 8 pm), which span four seasons in two years. Also, the various types of steam, which can be similar to smoke and can be identified with air quality grassroots communities in installing the camera network. We used a camera network on various sites since early 2017 to monitor industrial activities of petroleum coke plants (Figure 1, left). We collaborated with air quality grassroots communities in installing the cameras, which capture an image approximately every 10 seconds. These images were streamed back to our servers for stitching into panorama images and stacking into timelapse videos. From these panorama images were streamed back to our servers for stitching into panorama images, which capture an image approximately every 10 seconds. These images were streamed back to our servers for stitching into panorama images and stacking into timelapse videos. From these panorama images, we cropped clips based on domain knowledge about where the smoke emissions frequently occur. Finally, these clips were labeled by citizen scientists (volunteers) to indicate whether smoke emissions are present by using an web-based video labeling system that we developed (Figure 2 and 3).

RISE consists of clips from 30 different days in the daytime (6 am to 8 pm), which span four seasons in two years. Also, the labeled video clips contain 19 different views cropped from three panoramas taken by cameras at three distinct locations. The dataset covers various characteristics of smoke emissions, including opacity and color, under diverse weather (e.g., haze, fog, snow, cloud) and lighting conditions. Moreover, the dataset involves distractions of various types of steam, which can be similar to smoke and can be challenging to distinguish. Figure 1 shows sample clips. We used the dataset to train an Inflated 3D Convolutional Neural Network (I3D ConvNet) as a baseline benchmark. We also applied Grad-CAM to visualize activated regions, which help us diagnose if the network can focus on areas that have smoke emissions. Also, we compare the labeling quality among citizen scientists and Amazon Mechanical Turkers (Mturkers). The code and the RISE dataset for training the network2 are all open-sourced and available for public access, same for the video labeling system3.

### 2 RELATED WORK

We have discussed the existing datasets for smoke recognition. This section provides an overview of existing smoke recognition techniques and citizen science.

A set of prior works relied on motions, colors, physical-based models, or hand-crafted features for smoke recognition. For instance, Kopilovic et al. computed the entropy of the optical flow field to identify smoke [31]. Celik et al. used color models to identify smoke pixels [10]. Toreyin et al. combined background subtraction, edge flickering, and texture analysis into a final result [52]. Lee et al. used change detection to extract candidate regions, computed feature vectors based on color modeling and texture analysis, and trained a support vector machine classifier using these features [32]. Tian et al. presents a physical-based model and use sparse coding to extract reliable features for single image smoke detection [51]. Gubbi et al. and Calderara et al. applied texture descriptors, such as a wavelet transform, on small blocks in an image for obtaining feature vectors and train a classifier using these features [8, 17].

Another set of prior works developed or enhanced various deep learning architectures for smoke recognition. For example, Yuan et al. trained two encoder-decoder networks to focus on global contexts and fine details, respectively, for smoke region segmentation [61]. Hu and Lu trained spatial-temporal ConvNets (similar to the two-steam model in action recognition [49]) and applied multi-task learning to avoid computing optical flow for real-time detection [24]. Liu et al. fused ResNet (trained with the original RGB images) and ConvNet

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1. [https://github.com/CMU-CREATE-Lab/Deep-Smoke-Machine](https://github.com/CMU-CREATE-Lab/Deep-Smoke-Machine)
2. [https://github.com/CMU-CREATE-Lab/video-labeling-tool](https://github.com/CMU-CREATE-Lab/video-labeling-tool)
3. [https://github.com/CMU-CREATE-Lab/video-labeling-tool](https://github.com/CMU-CREATE-Lab/video-labeling-tool)

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| # of scenes | # of labeled clips | # of frames (images) | Average # of frames per clip | Ratio of smoke frames | Has temporal data? | Has context? | Is from industrial sources? | Appearance change level |
|-------------|--------------------|----------------------|-------------------------------|-----------------------|-------------------|-------------|---------------------------|------------------------|
| This Work   | 19                 | 12,567               | 452,412                       | 36                    | 41%               | yes         | yes                       | high                   |
| Bugarić et al. [6] | 10                | 10                   | 213,909                       | 21,391                | 100%              | yes         | no                        | low                    |
| Ko et al. [30, 53] | 16                | 16                   | 43,090                        | 1,514                 | 37%               | yes         | yes                       | low                    |
| Dimitropoulos et al. [12, 16] | 22               | 22                  | 17,722                        | 806                   | 56%               | yes         | no                        | low                    |
| Toreyin et al. [11, 52] | 21               | 21                  | 18,031                        | 820                   | 98%               | yes         | yes                       | low                    |
| Filonenko et al. [15]* | ... | 396                 | 100,968                       | 255                   | 61%               | yes         | no                        | low                    |
| Xu et al. [57, 62] | ...              | ...                 | ...                           | ...                   | 49%               | no          | yes                       | no                     |
| Xu et al. [55, 62] | ...              | ...                 | ...                           | ...                   | 100%              | no          | yes                       | low                    |
| Xu et al. [56, 62] | ...              | ...                 | ...                           | ...                   | 50%               | no          | yes                       | low                    |
| Bai et al. [5]* | ...              | ...                 | ...                           | ...                   | 16%               | no          | no                        | medium                 |
| Lin et al. [34, 62]* | ... | 16,647              | ...                           | ...                   | 29%               | no          | no                        | low                    |
| Yuan et al. [14, 60]* | ... | 24,217              | ...                           | ...                   | 24%               | no          | no                        | low                    |
Table 2: The number and ratio of video clips for all 19 camera views filtered by various temporal conditions.

| Condition          | # of labeled clips | Ratio |
|--------------------|--------------------|-------|
| Has smoke          | 5,090              | 41%   |
| In winter (Dec to Feb) | 7,292              | 58%   |
| In spring (Mar to May) | 1,057              | 8%    |
| In summer (Jun to Aug) | 2,999              | 24%   |
| In fall (Sep to Nov)  | 1,219              | 10%   |
| From 6 am to 10 am   | 4,001              | 32%   |
| From 11 am to 3 pm   | 6,071              | 48%   |
| From 4 pm to 8 am    | 2,495              | 20%   |

Table 3: Ratio of the number of videos for each split (rounded to the nearest second digit). Split $S_0$, $S_1$, $S_2$, $S_4$, $S_5$ is based on scenes. Split $S_3$ is based on time sequence.

| Split | $S_0$ | $S_1$ | $S_2$ | $S_3$ | $S_4$ | $S_5$ |
|-------|-------|-------|-------|-------|-------|-------|
| Training | .62   | .62   | .62   | .61   | .62   | .62   |
| Validation | .13   | .12   | .12   | .14   | .11   | .13   |
| Testing  | .25   | .26   | .26   | .25   | .26   | .25   |

3 RISE DATASET

This paper introduces RISE, the first large-scale video dataset for recognizing industrial smoke emissions. RISE dataset consists of 12,567 labeled clips from industrial sources, including those emitted from stacks (i.e., stack emission) and escaped from facilities (i.e., fugitive emission). Each clip has 36 frames (with resolution 180 by 180 pixels), which represent about 6 minutes in real-world time. These clips contain 19 distinct views (Figure 5), where 15 views are cropped from the panorama timelapse at one site, and 4 views are from two other sites. These clips span 30 days across four seasons in two years, from 6 am to 8 pm. Table 2 summarizes the distribution of this dataset across time.

This dataset has six splits ($S_0$ to $S_5$ in Table 3), and each split has three different training, validation, and testing sets. Most of the splits (except $S_3$) are based on scenes, where different views are used for each phase. For these splits, 15 views from one site are spread among all three sets, and four views from two other sites are always in the testing set. In this way, we can estimate the generalizability of models trained with this dataset. Split $S_3$ is based on time sequence, where the farthermost 18 days are used for training, the middle 2 days are used for validation, and the nearest 10 days are used for testing. Thus, we can evaluate if models trained with data in the past can be used in the future.

3.1 System for Data Collection

We have built and deployed cameras to monitor pollution sources (Figure 1, left). The physical system uses a Raspberry Pi single-board computer to control a Nikon 1 J5 digital camera. It also has...
We apply citizen science [26, 48] to invite volunteers to participate in with affected residents in person, and attended local events (e.g., volunteers who are not familiar with visual opacity reading [3]. Thus, volunteers to annotate data. Citizen science opens opportunities to collaborate with residents and advocacy groups, who have diverse expertise in local concerns. Through two workshops with air quality advocates, three presentations in local community events, and two guest lectures in universities, we recruited volunteers to help label smoke emissions using this labeling tool. The design and use of this tool were iteratively refined based on the valuable insights from these community members. For instance, we observed that volunteers enjoy labeling data on tablets. Thus we make sure that the tool works on most modern browsers (i.e., Chrome, Firefox, Safari, Edge) for recent operation systems, including Android, iOS, Safari, Edge) for recent operation systems, including Android, iOS, Windows, and Mac OS. Also, we found that the labeling task can be challenging for volunteers who are not familiar with visual opacity reading [3]. Thus, we implemented an interactive tutorial to introduce the task with step-by-step guidance (Figure 4). Users are first presented with simplified tasks that explain small concepts, such as the characteristics of smoke and the differences between smoke and steam. After performing each small task, the system shows the answers, explanations, and the regions on the clips that have smoke emissions.

There are two modes of user interfaces for data labeling. The first one (the individual mode) asks volunteers or researchers to label 16 video clips at once (Figure 2). Users can scroll the interface and click or tap on the video clips to indicate the presence of smoke emissions. The second one (the collaborative mode) asks researchers to confirm the labels contributed by volunteers. In the collaborative mode, the system shows the answers provided by citizens as prior information, and the researcher can choose to agree with or override these answers. This mode is designed to reduce the mental load for the labeling task and increase the speed of gathering labels at the early stage of system deployment when the amount of users is small.

When labeling, we refer to the 16 clips provided by the system as a page. For quality control, we randomly insert four gold standards (labeled by the researcher), and the system will accept a page and record its labels if the volunteer answers all the gold standards correctly. Otherwise, the page will be discarded. We make sure that at least one negative and positive samples are included in the gold standards to prevent uniform guessing. Besides, each clip is reviewed by at least two different volunteers (identified using Google Analytics tracker). If their answers do not agree with each other, a third volunteer is asked to review the clip. The system takes the majority vote of the answers as the final label for the clip. For information security, we encoded the pages and their labels into JSON Web Tokens with digital signatures issued by the back-end server. Combining with the https protocol, we make sure that the labels sent from the front-end are authentic and valid.

3.3 Analysis of User Contribution
The stable version of the labeling tool was launched in early February 2019. Up to February 24 in 2020 (12 months), the tool has collected 12,567 fully-labeled and 11,402 partially-labeled clips. The partially labeled clips were reviewed by only one volunteer or two volunteers with disagreement, and we did not include them in the dataset due to uncertain data quality. Among the fully-labeled video clips, 42% (5,230) and 20% (2,560) of the data are labeled individually by researchers and citizens, respectively, and 38% (4,777) of them are labeled collaboratively.

During the launch period of nine months, we attract 60 volunteers who contributed at least one page that passed the system’s quality check. We divide the volunteers into four groups based on their reliability (the acceptance rate of pages) and contributions. For instance, volunteers in the top enthusiast group have higher reliability (greater than or equal to 0.5) and a higher number of accepted pages (greater than or equal to the average of all participants). The analysis of user groups shows that 12% of them contributed 86% of the data, which shows a highly skewed pattern of contribution (Table 4). This group of active users also have high reliability (mean=76, std=10), which is the acceptance rate of the labeling pages. This skewed pattern is typical among citizen science projects, where many volunteers participate for only a few times [46].

3.2 System for Data Annotation
We apply citizen science [26, 48] to invite volunteers to participate in this research and develop a web-based smoke labeling tool to allow volunteers to annotate data. Citizen science opens opportunities to collaborate with residents and advocacy groups, who have diverse expertise in local concerns. Through two workshops with air quality advocates, three presentations in local community events, and two guest lectures in universities, we recruited volunteers to help label smoke emissions using this labeling tool. The design and use of this tool were iteratively refined based on the valuable insights from these community members. For instance, we observed that volunteers enjoy labeling data on tablets. Thus we make sure that the tool works on most modern browsers (i.e., Chrome, Firefox, Safari, Edge) for recent operation systems, including Android, iOS, Windows, and Mac OS. Also, we found that the labeling task can be challenging for volunteers who are not familiar with visual opacity reading [3]. Thus,
Table 4: Analysis of the volunteers who contributed at least one page that passes the quality check and accepted by the system. The format for the 4th and 6th columns is “mean ± standard deviation”. Reliability means the acceptance rate of pages (with 16 clips).

| User group      | # of users | Reliability ∀ group | Reliability ∀ user | # of accepted pages ∀ group | # of accepted pages ∀ user |
|-----------------|------------|----------------------|--------------------|-----------------------------|---------------------------|
| Top Enthusiasts | 7 (12%)    | .86 ± .10            | 1,491 (86%)        | 213 ± 328                   |
| Other Enthusiasts |          | ...                  | ...                | ...                         |
| Top Volunteers  | 41 (68%)   | .69 ± .19            | 218 (13%)          | 5 ± 5                       |
| Other Volunteers| 12 (20%)   | .26 ± .08            | 18 (1%)            | 2 ± 1                       |
| All             | 60 (100%)  | .81 ± .25            | 1,727 (100%)       | 29 ± 125                    |

Table 5: The data quality (simulated 100 times) of citizens and MTurkers, using researcher labels as the ground truth. The results are based on 392 positive labels with smoke (54.4% out of total N=720 videos). Filtered MTurker is the one with reliability larger than 0.3. The reported format is “mean ± standard deviation.”

| User group          | Precision | Recall | F-score     |
|---------------------|-----------|--------|-------------|
| Citizen             | .98       | .83    | .90         |
| Filtered MTurker    | .94±.01   | .89±.01| .91±.01     |
| All MTurker         | .93±.01   | .83±.01| .88±.01     |

Table 6: The inter-rater agreement (simulated 100 times) of the labels between pairs of MTurker, citizen, and researcher groups. The reported format is “mean ± standard deviation.”

|                    | Cohen’s kappa |
|--------------------|---------------|
| Researcher v.s. Citizen | .80           |
| Researcher v.s. Filtered MTurker | .81±.01 |
| Researcher v.s. All MTurker   | .75±.02      |
| Citizen v.s. All MTurker     | .72±.02      |
| Citizen v.s. Filtered MTurker| .75±.01      |

3.4 Analysis and Comparison of Data Quality

We compare the labels produced by three groups: citizens (volunteers), researchers, and crowd workers (MTurkers). First, we randomly sampled 720 clips that were fully-labeled by both citizens and researchers from a subset of the RISE dataset. Clips in this subset were randomly selected from 10,625 videos that had been labeled between February 2019 and November 2019. We then divided these clips into 60 labeling tasks and added four randomly-sampled gold standards to each task for quality control. The user interface is identical to the one used for citizens. When labeling, we ensured that the MTurkers took the interactive tutorial before performing the task. We first posted the tutorial task with 50 assignments to Amazon Mechanical Turk (MTurk) ($1.5 per task) and granted qualifications to the workers who finished the tutorial. We then posted the 60 labeling tasks to MTurk, where each task collects five assignments from different MTurkers. Only the workers who have the qualification can perform our tasks. The estimated time to complete one task is 90 seconds. We paid $0.25 per task, yielding an estimated hourly wage of $15. As a result, 14 MTurkers were recruited and accomplished all the tasks in about 12 hours.

The data quality is similar between citizens and filtered MTurkers. The filtered MTurkers is a subset with reliability (i.e., the acceptance rate of the labeling pages) better than 0.3 (random guessing is 0.07). To match the quality-control mechanism used in the deployed labeling tool, we randomly selected 3 assignments for majority voting and simulated for 100 times. Using researcher labels as the ground truth, Table 5 indicates similar strong performance in precision, recall, and f1-score of the positive labels (with smoke). Also, the strong Cohen’s kappa in Table 6 shows a high inter-rater agreement.

4 EXPERIMENTS

We establish a baseline benchmark for RISE dataset by exploiting Inflated 3D Convolutional Neural Network (I3D ConvNet) with Inception-v1 layers [9]. I3D is a representative model for video action recognition based on the inflation of 2D ConvNet. The inputs of this baseline model are RGB frames. The parameters of this model are pretrained on ImageNet [45] and Kinetics [29] datasets, and then finetuned on the training set of RISE. During training, we apply data augmentation techniques, including horizontal flipping, random resizing and cropping, perspective transformation, area erasing, and color jittering. We refer to this baseline model as RGB-I3D. The validation set is used for hyper-parameter tuning.
Table 7: F-scores for comparing the effect of data augmentation on the testing set for each split. Abbreviation ND means no data augmentation.

| Model         | S0 | S1 | S2 | S3 | S4 | S5 | Average |
|---------------|----|----|----|----|----|----|---------|
| RGB-I3D       | .80| .84| .82| .87| .82| .75| .817    |
| RGB-I3D-ND    | .76| .79| .81| .86| .76| .68| .777    |
| RGB-SVM       | .57| .70| .67| .67| .57| .53| .618    |

Table 8: F-scores for comparing the effect of using temporal information on the testing set for each split. Abbreviation FP means with frame perturbation.

| Model         | S0 | S1 | S2 | S3 | S4 | S5 | Average |
|---------------|----|----|----|----|----|----|---------|
| RGB-I3D       | .80| .84| .82| .87| .82| .75| .817    |
| RGB-I3D-FP    | .76| .81| .82| .87| .81| .71| .797    |
| Flow-I3D      | .55| .58| .51| .68| .65| .50| .578    |
| Flow-SVM      | .42| .59| .47| .63| .52| .47| .517    |

4.1 Implementation

The parameters of our baseline models are optimized using binary cross-entropy loss and Stochastic Gradient Descent (SGD) with momentum 0.9 for 2,000 steps. Table 10 shows the detail setup of training hyper-parameters. For each step, we perform gradient descent to update the parameters after accumulating the gradients for several iterations (using backward propagation) with a specific batch size. We apply weight decay (regularization) when training the model to prevent overfitting. The initial learning rate starts from a fixed value and decreases by a factor of 0.1 based on predefined milestones. All of the models and training scripts are implemented in PyTorch framework [40], and executed on one machine with four NVIDIA GTX 1080 Ti GPUs. Batch sizes are evenly distributed among all GPUs. When comparing performance among different models, we select the one with the best F-score after 500 training steps. For models that have the same F-score, we select the one with the lowest validation error.

4.2 Result

In order to understand the effectiveness of our baseline, we also train five other models for comparison.

- RGB-I3D-ND is the same baseline model without any data augmentation.
- RGB-SVM exploits Support Vector Machine (SVM) as the classifier, which takes the pretrained I3D features (without finetuning on our dataset) as input.
- RGB-I3D-FP is trained using video clips with frame-wise random permutation.
- Flow-I3D has the same network architecture as our baseline, but processes precomputed TVL1 optical flow frames. It also conducts the same data augmentation pipeline except color jittering.
- Flow-SVM, similar to RGB-SVM, uses raw I3D features extracted with optical flow frames.

The implementation details of these I3D models are the same as the aforementioned. For the deep neural network models that are not mentioned in Table 10, they use the same hyper-parameters as the RGB-I3D model. From the experiment results, we can make the following observations. First, results in Table 7 show that the I3D model outperforms SVM by a large margin, and data augmentation can further improve the performance. Second, from results in Table 8, we can see that frame-wise permutation does not degrade the performance much, and Flow-based models perform worse than their RGB counterparts. This observation indicates the challenge of using temporal information within this dataset. To further understand this challenge, we train the other five variations based on RGB-I3D with different temporal processing techniques.

- RGB-I3D-NL wraps two Non-Local (NL) blocks [54] in the last Inception layer (closest to the output) around the 3D convolution blocks with kernel size larger than one. NL blocks are designed to capture long-range dependencies by modeling interactions among features in both space and time.
- RGB-I3D-TSM wraps Temporal Shift modules (TSM) [35] around each Inception layer. This TSM variation shifts 1/4 of the channels along the temporal dimension. This shifting technique is proposed to facilitate exchanging information among nearby video frames.
- RGB-I3D-TC attaches one Timeception (TC) layer [25] after the last Inception layer, using 1.25 as the channel expansion factor. This variation is our best baseline model (Table 11). TC is designed to learn long-range dependencies with simplified and multi-scale kernels, where each convolution kernel has a different scale and is operated on only one temporal dimension. We fine-tune this TC variation from the best RGB-I3D model with the I3D layers frozen.
- RGB-I3D-TSM wraps Temporal Shift modules (TSM) [35] around each Inception layer. This TSM variation shifts 1/4 of the channels along the temporal dimension. This shifting technique is proposed to facilitate exchanging information among nearby video frames.

Results in Table 9 indicate that these techniques do not outperform the baseline model significantly, which confirms the challenge of using the temporal information.

4.3 Visualization

To verify the semantic concept captured by our baseline model, we apply the Gradient-weighted Class Activation Mapping (Grad-CAM [47]) for visualization. This technique analyzes the gradient signal that flowed into the last convolutional layer and generates a localization heatmap, which highlights the important areas for prediction. Ideally, our model should focus on the regions identifying smoke emissions, instead of other objects in the background (e.g., stacks, plant facilities). Therefore, we show true positive cases for fugitive emissions (Figure 6), stack emissions (Figure 8), and co-existence of both smoke and steam (Figure 7). Also, we show a false positive case when steam looks like smoke (Figure 9), another false positive case that cloud shadow is misclassified as smoke (Figure 10), and a negative case where the smoke emission has a small amount for a short duration (Figure 11). These figures show the time sequence from left to right, sampled from 36 frames for every 9 frames.
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Table 9: F-scores for comparing different types of temporal models. Abbreviation NL means the Non-Local module [54]. Abbreviation TSM indicates the Temporal Shift module [35]. Abbreviation TC and LSTM means adding the Timeception layers [25] and the Long Short-Term Memory layers [19], respectively.

| Model         | $S_0$ | $S_1$ | $S_2$ | $S_3$ | $S_4$ | $S_5$ | Average |
|---------------|-------|-------|-------|-------|-------|-------|---------|
| RGB-I3D       | .80   | .84   | .82   | .87   | .82   | .75   | .817    |
| RGB-I3D-TSM   | .81   | .84   | .82   | .87   | .80   | .74   | .813    |
| RGB-I3D-LSTM  | .80   | .84   | .82   | .85   | .83   | .74   | .813    |
| RGB-I3D-NL    | .81   | .84   | .83   | .87   | .81   | .74   | .817    |
| RGB-I3D-TC    | .81   | .84   | .84   | .87   | .81   | .77   | .823    |

Table 10: Hyper-parameters. Symbol $\eta$ and $i$ indicate the initial learning rate and gradient accumulation iterations, respectively. Milestones are the global steps to decrease the learning rate by a factor of 0.1.

| Model         | $\eta$ | Weight decay | $i$ | Batch size | Milestones               |
|---------------|--------|--------------|-----|------------|--------------------------|
| RGB-I3D       | 0.1    | $10^{-6}$    | 2   | 40         | (500, 1500)              |
| RGB-I3D-TSM   | 0.1    | $10^{-10}$   | 1   | 40         | (1000, 2000)             |
| RGB-I3D-LSTM  | 0.1    | $10^{-4}$    | 1   | 32         | (1000, 2000)             |
| RGB-I3D-NL    | 0.1    | $10^{-6}$    | 2   | 40         | (500, 1500)              |
| RGB-I3D-TC    | 0.1    | $10^{-6}$    | 1   | 32         | (1000, 2000)             |

Table 11: Evaluation of the best baseline model (RGB-I3D-TC) on the testing set for each split. ROC/AUC means area under the receiver operating characteristic curve.

| Metric       | $S_0$ | $S_1$ | $S_2$ | $S_3$ | $S_4$ | $S_5$ | Average |
|--------------|-------|-------|-------|-------|-------|-------|---------|
| Precision    | .87   | .84   | .92   | .88   | .88   | .78   | .862    |
| Recall       | .76   | .83   | .77   | .87   | .76   | .76   | .792    |
| F-score      | .81   | .84   | .84   | .87   | .81   | .77   | .823    |
| ROC/AUC      | .90   | .94   | .94   | .95   | .92   | .91   | .927    |

5 DISCUSSION

Exploiting Temporal Information. The experiment results show that the temporal information in our dataset is challenging to utilize. The visualization also shows that the model has limitation in excluding steam (Figure 9), omitting fast-moving cloud shadow (Figure 10), and identifying small-amount smoke emissions (Figure 11). This limitation may come from the difficulty of finding clear correspondence points across frames because smoke emissions, unlike objects, have dynamic and ambiguous shapes. Moreover, our data have a low temporal resolution (10 seconds in real-world time per frame), which means that the pixel displacements are large and can exacerbate this difficulty. Developing methods to efficiently use the temporal information in timelapse videos for smoke-like particles remains an open research question.

Lesson Learned from the Citizen Science Approach. When collecting the RISE dataset with the citizen science approach, we encountered challenges that may offer implications when developing AI systems for social good. First, setting up cameras to collect air pollution dataset requires substantial community outreach efforts since people who were severely affected by air pollution tend to be financially impoverished. To them, improving local air quality may not be their top priority. Second, industrial smoke emissions, unlike general object recognition, are not intuitive to identify. From the two workshops that we collaborated with air quality advocacy groups in labeling smoke, we found that the task requires training to understand the color, opacity, and motion of smoke. Third, air pollution issues, unlike other citizen science projects in astronomy (e.g., Galaxy Zoo [36]) or bird watching (e.g., eBird [50]), may not be enjoyable. This characteristic makes it hard to push out this smoke labeling project to the general public. One possible direction is to recruit MTurkers for collecting labels. However, citizen science has been proven useful in empowering residents to address air pollution [20, 21]. Inviting community members to label data
Integrating Citizen Science and Crowdsourcing. The analysis of data quality demonstrates similar performance between citizen scientists and Mturkers. This result suggests new opportunities for integrating citizen science and crowdsourcing due to their resembling data quality. For instance, at the early stage of system development, if there is a need to develop a model that can generate visual evidence to motivate volunteers, one can recruit MTurkers to label an initial small-scale dataset. Once the model is trained with the initial dataset, one can use it to produce evidence that can attract active citizen scientists who are willing to contribute data. At this stage, the model accuracy may not reach the desired level, and human intervention may need to be involved. However, as the community’s attention starts to increase, it would be possible to collect more labels and improve model performance over time. A future direction is to ask expert citizens who received the training of visual opacity reading [3] to provide finer labels, such as the opacity and shape of smoke.

Limitations. This work has several limitations. First, in the data quality analysis, it may be unfair to compare the reliability between citizens and MTurkers directly. Due to the difference in their label aggregation logic, it is impossible to know the exact number of volunteers who completed the selected 720 video clips in the analysis. Second, our dataset does not include nighttime video clips, which are difficult for human eyes to identify due to insufficient light. Third, this dataset currently does not offer bounding box labels. We applied domain knowledge to predetermine the locations that smoke emissions were likely to occur, which makes smoke recognition a classification instead of a detection problem. Finally, there exist other ways for aggregating labels provided by researchers and citizens, such as EM-based methods [42]. In our case, researchers always override the decisions made by citizens. We leave the expansion of the different label types and also the methodology for aggregation decisions from different user groups to future work.

6 CONCLUSION

We have described a new large video dataset for recognizing industrial smoke emissions. By collaborating with citizen scientists, we have annotated 12,567 clips that contain 19 views and span 30 days across seasons in two years. The abundant temporal appearance changes of smoke emissions and other distractions (e.g., steam) under various weather conditions open research opportunities for using Computer Vision in addressing air pollution issues. Using this dataset, we have trained an Inflated 3D Convolutional Neural Network as the baseline model for comparison. We have found that it is challenging to use the temporal information in this dataset efficiently. By randomly choosing a subset for comparing data quality, we have found that citizen scientists and Amazon Mechanical Turkers have similar reliability. These findings suggest possible future directions in model improvements and new collaboration methods between citizen science and crowdsourcing.

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