Reply on RC2

Dear Editor and Reviewers,

Thank you for the comments.
We gratefully thank the editor and all reviewers for their time spent making their constructive remarks and useful suggestions, which has significantly raised the quality of the paper and has enabled us to improve the paper. Each suggested revision and comment brought forward by the reviewers was considered and incorporated. We will be happy to edit the text further based on helpful comments from the reviewers.
The text style for revision is as follows:

- All comments are in **black**.
- All responses to the comments are in **blue**.
- All pages and line numbers refer to the revised manuscript.
- All revised contents in the manuscript are highlighted in **red**.

1. This paper uses a camera system to detect hydrometeor types such as RN, SN, and GR. Uses ML techniques but not clear how it is trained using observed input parameters.

Reply:

Thanks for the comments.

The surveillance video is divided into 5-second segments. Within each segment, sequences of 5, 10, and 15 frames are selected and fed into the spatial feature extraction module (the effect of sequence length on the classification results is discussed in Section 4.4). The extracted feature vectors are then input into the temporal model for precipitation type classification. We have added these description in lines 269-277.

2. Camera systems can provide yes or no question on RN, SN, or FG detection (see Gultepe et al 2009AMS Bull, AMS Monographs on Solid precipitation 2017; AMS Bull Ice fog (2014). But doesnt provide any other info on particle shape, size, and cncentration.

Reply:

Thanks for the comments.

Based on the authors' understanding of surveillance camera imaging principles, researchers can extract information such as droplet size, droplet spectra, and other microphysical characteristics of precipitation, provided they have access to the necessary camera parameters.

For example, the following studies demonstrate how cameras can be employed to calculate the Drop Size Distribution and other microphysical properties of precipitation.

- Allamano, P., Croci, A. and Laio, F., 2015. Toward the camera rain gauge. Water Resources Research, 51(3): 1744-1757.
- Jiang, S., Babovic, V., Zheng, Y. and Xiong, J., 2019. Advancing opportunistic sensing in hydrology: A novel approach to measuring rainfall with ordinary surveillance cameras. Water Resources Research, 55(4): 3004-3027.
- Wang, X., Wang, M., Liu, X., Zhu, L., Glade, T., Chen, M., Zhao, W. and Xie, Y., 2022. A novel quality control model of rainfall estimation with videos–A survey based on multi-surveillance cameras. Journal of Hydrology, 605: 127312.

The above three studies primarily focus on precipitation captured by daytime visible-light surveillance videos, whereas the following study specifically examines nighttime precipitation.

- Lee, J., Byun, J., Baik, J., Jun, C. and Kim, H.-J., 2022. Estimation of raindrop size distribution and rain rate with infrared surveillance camera in dark conditions. Atmospheric Measurement Techniques Discussions: 1-23.

3. Looking at the only visible images cant resolve the particle discrimination issue.

Reply:

Thanks for the comments.

Please refer to the response to Question2.

Therefore, we attempt to distinguish precipitation phases using image-based analysis. This approach is based on the fact that different precipitation types exhibit distinct visual characteristics in surveillance footage, such as variations in brightness, shape, size, and motion patterns. By leveraging these features, we aim to classify precipitation phases more effectively.

4. Visually helps what is on the ground if Visibility lows but many times this cant be true because during precip Vis goes down.

Reply:

Thanks for the comments.

The increase in precipitation intensity and variations in ambient lighting conditions does affect visibility (as analyzed in section 4.6). It is important to clarify that surveillance cameras capture visible-light videos during the daytime, while at night or under low-light conditions, they record near-infrared videos to achieve imaging in the monitored area, enabling "night vision" functionality.

As shown in Figure 12, our experiments cover various precipitation scenarios from daytime to nighttime and across different intensities. These include conditions ranging from drizzle to heavy rain with an intensity of up to 110 mm/h, from light snow to blizzards with a precipitation intensity of approximately 20 mm/h, and graupel events with an intensity of 12 mm/h. As discussed in lines 533–542, we have compared the performance of our method under these conditions. Experimental results indicate that while performance varies under different visibility conditions, the proposed method remains generally stable overall.

5. This is well know that Vis doesnt provide precip type or amount unless you know the particle type. In reality, all your analysis is based on visibility of light reflected/scatterered due to hydrometeors.

Reply:

Thanks for the comments.

In response, the authors Need evidence that our method leverages the reflection and scattering of light by precipitation particles, which manifest in surveillance videos as differences in particle shape, color, and brightness—key spatial features for distinguishing precipitation types. Additionally, we utilize the falling speed of particles, as meteorological studies have established that different particles exhibit varying fall velocities. As described in Section 3.1.2 on the temporal feature extraction module, we enhance the accuracy of phase differentiation by incorporating these temporal variations, such as fall speed, alongside the spatial characteristics of precipitation particles.

6. It is clear that we can detect precip for yes or no with help of a Temp probe. Therefore, i feel this manuscript needs to be reduced significantly focusing on the clear objectives. Otherwise, this kind of work can lead to very limited applications.

Reply:

Thanks for the comments.

We appreciate the reviewer’s suggestion on the temperature inclusion of our work. Certainly, incorporating temperature measurements could potentially enhance the accuracy of the results, and this is something that could be explored in future work.

However, our study focuses solely on utilizing surveillance video data to distinguish between rain, snow, and graupel through deep learning methods. The primary motivation behind this research is to take advantage of surveillance cameras with their large number, high density, and fast transmission capabilities. Additionally, this approach can be implemented using existing urban surveillance resources, which helps reduce both maintenance and installation costs. Since temperature measurements are not typically available from surveillance cameras, we focus on the visual characteristics of precipitation captured in the videos. This offers a novel solution for various urban environments, providing continuous rain, snow, and graupel monitoring with low deployment costs.

There are several issues in the paper:

1. captions are not clear enough to provide detailed info on figs.

Reply:

We have made careful revisions to the figure captions in the manuscript. Please refer to the revised version.

2. Velociry means what?

Reply:

We did not find the word "Velociry" in our manuscript. We assume you meant "velocity," which in this context refers to the terminal velocity of particles as they fall towards the ground. We have already added this clarification in the revised manuscript.

3. what 2 diff graupel types have very large diffs?

Reply:

We apologize, but we find it difficult to understand the meaning of this sentence. We would greatly appreciate it if you could point out the specific page or line.

We can only speculate that you are referring to the differences in graupel types shown in Figure 7. In this case, we have added relevant references. Figure 7 was primarily created based on meteorological research findings, and we have included additional information in the figure caption to clarify that this study focuses on solid-state graupel particles.

4. Issues with blowing snow and fog are not discussed (Gultepe et al Pure and Appl Geop 2018 Aviation Meteorology) and not provided.

Reply:

Thanks for the comments. We have discussed the impact of wind on precipitation phase differentiation, and snow is, of course, included. Please see lines 555-601.

Fog is outside the scope of our focus, so it was not addressed. However, we have acknowledged the interference caused by fog to our method in the discussion section, as it represents a special case where the method fails to perform effectively. Please see section 4.6.

5. about 90% success in the results to me is too high, it can be ok for yes or no for precip but not the type discrimination.

Reply:
Thank you for your valuable feedback.
We understand your concern regarding the reported 90% success rate in the results. As an example from the articles cited in our paper, Khan et al. (2022) used the ResNet18 architecture and achieved an unprecedented overall detection accuracy of 97% for weather detection. Ibrahim et al. (2019) proposed a new framework called WeatherNet, which achieved an accuracy of over 90%. Xiao et al. (2021) introduced a novel deep CNN, MeteCNN, for weather phenomena classification, which achieved an accuracy of 92%. These studies demonstrate the excellent performance of deep learning methods in weather detection and classification tasks,

While it may seem high for precipitation type discrimination at first glance, the reported accuracy of 90% is consistent with the results of previous studies in the field, such as those by Khan et al. (2022) and Ibrahim et al. (2019), where similar or even higher accuracies were achieved. This level of accuracy is based on a robust dataset and extensive model fine-tuning. It is important to acknowledge that distinguishing between different types of precipitation is inherently more complex than a simple yes/no classification. The 90% accuracy reflects the overall performance, but additional metrics such as precision, recall, and confusion matrices are provided to give a more nuanced understanding of the model's performance across different precipitation types. Moreover, our method comprehensively integrates both the image features and temporal characteristics of different precipitation types. A detailed analysis of error cases is also included, identifying specific precipitation types where the model's performance may be less reliable, and providing insights into potential reasons for these limitations, such as ambiguities in visual features or challenging environmental conditions. Therefore, achieving this level of accuracy is well-supported by sufficient evidence.

Reference:

Khan, M.N., Ahmed, M.M.J.I.j.o.t.s. and technology, 2022. Weather and surface condition detection based on road-side webcams: Application of pre-trained convolutional neural network. 11(3): 468-483.

Ibrahim, M.R., Haworth, J. and Cheng, T.J.I.I.J.o.G.-I., 2019. WeatherNet: Recognising weather and visual conditions from street-level images using deep residual learning. ISPRS International Journal of Geo-Information, 8(12): 549.

Xiao, H., Zhang, F., Shen, Z., Wu, K. and Zhang, J., 2021. Classification of weather phenomenon from images by using deep convolutional neural network. Earth and Space Science, 8(5): e2020EA001604.

5. did you provide a field campaign prediction analysis for particle detection?

Reply:

Thanks for the comments.

We provide a comparative analysis in Section 4.5.

The starting point of our research is to leverage the high spatiotemporal resolution and low-cost observational advantages of urban surveillance cameras. Therefore, real-world observations primarily focus on cameras deployed in urban areas. As shown in Figure 11, the scene captured by Surveillance Camera 2 is more representative of a rural environment, with fewer buildings and less human activity.

6. Finally, definition of direct and indirect is not clear to me. Direct to me if you can measure parameters using insitu sensors. indirect means you get the results based on secondary products.... This needs to be improved.

Reply:

Thank you for raising this issue. In response to a similar suggestion from Reviewer 1, we have addressed this in Section 2.

Direct measurement methods focus on the image/video features exhibited during the precipitation particle's falling process, while indirect measurements involve snow or water accumulation on the ground. For example, indirect measurements focus on whether there is snow on the ground rather than whether it is snowing.

8. Haze related text needs to be improved, abd cant be a hydrometeor type!!! if it is not wet particle.

Reply:

Thank you for the reminder. We have removed the mention of haze.

Finally, we would like to express our sincere gratitude to your insightful comments and constructive suggestions. Your valuable feedback has greatly contributed to enhancing the clarity and quality of our manuscript, and we truly appreciate the time and effort you dedicated to reviewing our work.