Wu et al. present a global daytime and nighttime low cloud morphology dataset classified based on deep learning methods. The work builds on the algorithms of Yuan et al. (2020; for deep learning) and Wang et al. (2022; for nighttime COT retrieval) to expand the range of cloud classification, for the first time, to nighttime retrievals. The dataset is novel, unique, and of high quality, with significant potential for use in cloud and climate studies. However, I find that the manuscript lacks some important information, particularly regarding their choice of testing data, sensitivity studies, and data screening techniques. Moreover, the data could be presented in a better way for a wider scientific community. Therefore, I recommend a major revision of the manuscript/dataset by addressing the following comments before it can be considered for potential acceptance in *ESSD*.

Comments:

1. While the TIR-CNN-based retrieval of cloud properties in Wang et al. (2022) could be a better one compared to the TIR-based algorithm, it cannot replace the standard daytime retrieval algorithm in MODIS. Therefore, to justify using the TIR-CNN-based COT used in training the MCC-classification, I suggest the authors include an additional validation in this study, which includes comparing their MCC classification with that from the outputs of a CNN trained on MODIS daytime COT. Even though I agree that the choice of TIR-CNN-based COT is methodologically justified to stay consistent in their application to both daytime and nighttime retrievals, the inclusion of this additional validation/sensitivity study will strengthen their results and the MCC classification dataset.

2. The authors use different numbers of samples in each MCC category to train the model. For example, (0.6 times) 9,900 labeled suppressed Cu are used compared to just (0.6 times) 3,548 solid stratus samples. Shouldn't this disparity impact the performance of the classification for different MCC categories? Can the authors comment on this?

3. Why do the authors interpolate the data within a 1°X1° scene to 128 X 128 pixels? Even if I consider the finest resolution of 1km, the number of pixels within a 1°X1° scene would be less than 128X128 pixels, leading to extrapolation-related truncation error. Also, did the authors perform any sensitivity test regarding the size of the scene considered in training the model except from 1°X1°? Wood and Hartmann (2006) use native MODIS 256 X 256 pixels in their classification. Increasing the grid size may reduce the probability of misclassifications (Fig. 3). For instance, considering a smaller domain may result in misclassification of edges of open cells into clustered Cu. In case you achieve a better classification, the resulting dataset can be resampled to a finer grid easily for future use in conjunction with other climate and weather-related datasets.

4. Information is missing regarding why channels 29, 31, and 32 were particularly used in training and classification when multiple other cloud-top-related channels (33-36) are available in MODIS.

5. What are the parallel yellow and red lines in the panels of Figure 4? Are these physical and being used in classification or graphics-related artefacts?

6. Regarding the dataset, I highly recommend using standard data formats used in atmospheric sciences like netCDF and HDF for easy cross-platform and cross-software accessibility. Not all users will be accustomed to the Python-specific NumPy format.

7. Since this is a data-descriptor paper, some important information on the contents (variables and how they are calculated) and the file nomenclature should be included in the manuscript. It may be presented as a separate sub-section within Section 2 and summarized using an additional table. This information is currently missing from the manuscript.

Minor comments:

1. Line 49-51: More recently Goren et al. (2019) showed a similar delay in closed-to-open transition using LES.

2. Line 60-61: The cloud morphology dataset by Wood and Hartmann (2006) has been expanded to more than a decade of MODIS observations, the Morphology Identification Data Aggregated over the Satellite-era (MIDAS), by McCoy et al. (2023).

3. Line 64: Abbreviation VGG not defined!

4. Line 64: "… for daytime scenes …". All the morphology datasets discussed prior to this point correspond to daytime observations, don't they?

5. Line 102-103: "Disorganized MCC … larger droplets and lower optical thickness." Can the authors cite studies that have demonstrated this fact?

6. Line 106: Citation missing!

7. Line 116: "spatial resolution of 1 km" This resolution is for nadir pixels. It changes with sensor zenith angle.

8. Line 121: The authors state that they filter out scenes with more than 10 % high clouds or ice clouds. How do the authors deal with ice/high cloud pixels in scenes where they are less than 10%? Are they set to missing values and not used in either training or classification steps?

9. Line 172: How is the reanalysis data co-located? Do you select the nearest timestamp or interpolated the data to MODIS observations?

10. A link to the classification dataset is missing in the "Data Availability" section.

11. No information on the file "example.xlsx" in the data repository.

Language-related suggestions:

Line 21: Abbreviation RFO defined in abstract is not used.

Line 84: dependent?

Line 91: Prior to "Section 2 intro…", perhaps insert an introductory sentence like "The manuscript is organized as follows."

Line 184: Abbreviation ML is not defined

Line 210: Remove underscore after Yuan et al. (2020)

Line 383: Consider changing the word "worse"

Line 409: "… nightly …" Do you mean nighttime?

References:

Goren, T., Kazil, J., Hoffmann, F., Yamaguchi, T., & Feingold, G. (2019). Anthropogenic air pollution delays marine stratocumulus break-up to open-cells. Geophysical Research Letters, 46, 14135–14144. https://doi.org/10.1029/2019GL085412

McCoy, I. L., McCoy, D. T., Wood, R., Zuidema, P., & Bender, F. A.-M. (2023). The role of mesoscale cloud morphology in the shortwave cloud feedback. *Geophysical Research Letters*, 50, e2022GL101042. https://doi.org/10.1029/2022GL101042

Wang, Q., Zhou, C., Zhuge, X., Liu, C., Weng, F., and Wang, M.: Retrieval of cloud properties from thermal infrared radiometry using convolutional neural network, Remote Sensing of Environment, 278, 113079, https://doi.org/10.1016/j.rse.2022.113079, 2022.

Yuan, T., Song, H., Wood, R., Mohrmann, J., Meyer, K., Oreopoulos, L., and Platnick, S.: Applying deep learning to NASA MODIS data to create a community record of marine low-cloud mesoscale morphology, Atmos. Meas. Tech., 13, 6989-6997, https://doi.org/10.5194/amt-13-6989-2020, 2020.