

Segmenteverygrain: A Python module for segmentation of grains in images

Zoltán Sylvester  ^{1,2¶}, Daniel F. Stockli  ², Nick Howes³, Kalinda Roberts⁴, Matthew A. Malkowski  ², Zsófia Poros⁵, Rowan C. Martindale  ², and Wilson Bai²

1 Bureau of Economic Geology, Jackson School of Geosciences, The University of Texas at Austin, Austin, TX, USA 2 Department of Earth and Planetary Sciences, Jackson School of Geosciences, The University of Texas at Austin, Austin, TX, USA 3 The Water Institute, New Orleans, LA, USA 4 BSC Group, Boston, MA, USA 5 ConocoPhillips, Houston, TX, USA ¶ Corresponding author

DOI: [10.21105/joss.07953](https://doi.org/10.21105/joss.07953)

Software

- [Review](#) 
- [Repository](#) 
- [Archive](#) 

Editor: Anastassia Vybornova 

Reviewers:

- [@pr4depr](#)
- [@jessepisel](#)

Submitted: 05 February 2025

Published: 08 August 2025

License

Authors of papers retain copyright and release the work under a Creative Commons Attribution 4.0 International License ([CC BY 4.0](#)).

Summary

Segmenteverygrain is a Python module that addresses the need for quantifying grain size in granular materials. It combines the Segment Anything Model (SAM) with a U-Net-style convolutional neural network to detect and measure grains or clasts in diverse image types, ranging from photomicrographs of sand, mineral grains, and thin sections to photographic images of gravel and boulder fields. Segmenteverygrain supports segmentation of large images, georeferencing, and interactive editing of the results.

Statement of need

Grain size and shape are key parameters that influence the physical and chemical properties of granular materials. Quantitative estimates of these parameters are important in a number of fields, including:

- geomorphology, sedimentology, stratigraphy, paleontology;
- subsurface reservoir quality;
- structural geology, petrology and geochemistry;
- civil engineering;
- environmental science;
- materials science.

In recent years, numerous studies have illustrated the promise of automated image analysis and/or machine learning (ML) approaches ([Azzam et al., 2024](#); [Buscombe, 2020](#); [Chen et al., 2023](#); [Mair et al., 2022, 2024](#); [Prieur et al., 2023](#); [Tang et al., 2020](#)). While these studies clearly show that ML techniques are superior to both manual data collection and conventional image processing techniques (e.g., [Purinton & Bookhagen, 2021](#)), they focus on a narrow range of image types, e.g., gravel on fluvial bars ([Mair et al., 2022, 2024](#)), boulder fields on planetary surfaces ([Prieur et al., 2023](#); [Robin et al., 2024](#)), or petrographic images ([Azzam et al., 2024](#); [Tang et al., 2020](#)).

With the emergence of large image segmentation models trained on millions of images (e.g., [Kirillov et al., 2023](#); [Ravi et al., 2024](#)), the opportunity arises to use these models to detect a variety of grains in a broad range of image types. Segmenteverygrain is a Python module that takes advantage of the Segment Anything Model (SAM) ([Kirillov et al., 2023](#)) and uses a U-Net-style convolutional neural network to create prompts for SAM. It ensures that the resulting masks contain no duplicates and do not overlap. In general, SAM masks are more

robust and accurate than the U-Net output ([Figure 1](#)). The U-Net model uses patches as input and output; to reduce edge effects, Hann-window-based weighting is used on overlapping patches ([Pielawski & Wählby, 2020](#)). The U-Net model was trained on 66 images of a variety of grains, split into 44,533 patches of 256x256 pixels. When compared to other approaches to grain size data collection, one of the advantages of Segmenteverygrain is that it is relatively easy to generate new training data and fine tune the U-Net model to improve the SAM output.

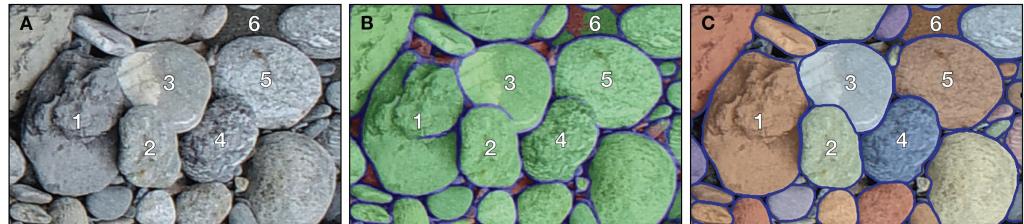


Figure 1: Photo of fluvial gravel (A), output of the U-Net segmentation (B), and the result of the SAM segmentation (C). The SAM segmentation correctly identifies grain 1 as a single object, separates grain 2 from grain 3 and grain 4 from grain 5, and incorrectly identifies a patch of the background as a grain (6). Image from Mair et al. ([2022](#)).

Segmenteverygrain has been successfully used on:

- images of boulder fields on asteroids ([Robin et al., 2024](#));
- photographs of gravel and cobbles on beaches ([Roberts, 2024](#)) and fluvial bars ([Figure 2](#));
- photomicrographs of sandstone ([Figure 3](#)) and oolitic limestone thin sections;
- photomicrographs of sand and detrital zircon grains.

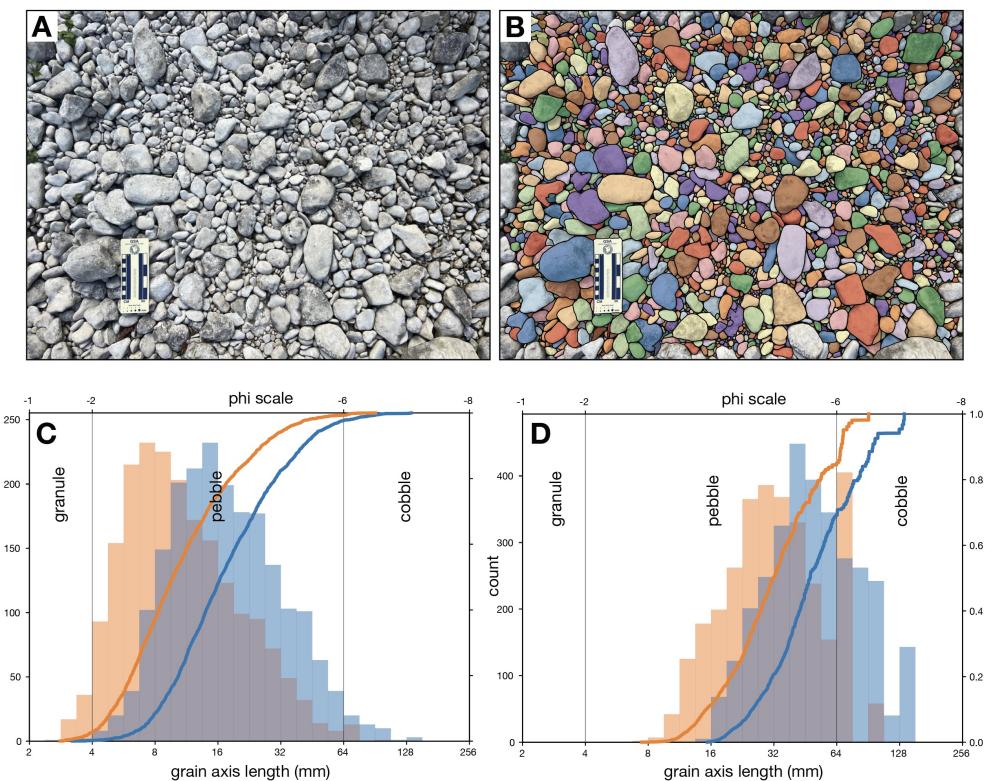


Figure 2: Photo of fluvial gravel (A), output of the segmentation (B), size distributions of the major and minor grain axes (C), and the area-weighted size distributions (D). Major grain axis lengths are shown in blue, minor grain axis lengths in orange. Photo taken by first author at Barton Creek, Texas.

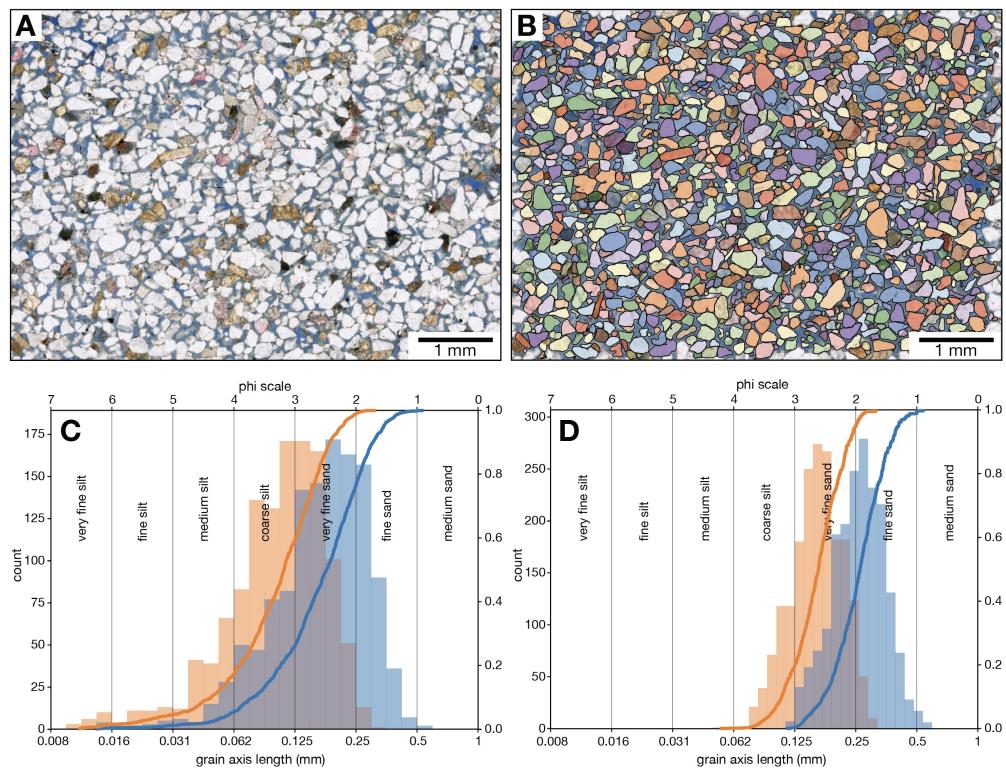


Figure 3: Photomicrograph of a sandstone in thin section (A), output of the ‘Segmenteverygrain’ segmentation (B), size distributions of the major and minor grain axes (C), and the area-weighted size distributions (D). Photomicrograph from Prodanovic et al. (2019).

Key functionality

The U-Net model in the Segmenteverygrain repository works relatively well on a variety of image types. However, it is recommended to first test it on a small image. If additional fine tuning is necessary, Segmenteverygrain has tools for interactively deleting, merging, and adding grains to generate training data.

The `predict_large_image` function can be used to run the segmentation of larger images that contain thousands of grains. This is done by running the U-Net + SAM predictions on smaller tiles of the input image, and collecting the grains into a list without duplicates.

Grain area, major and minor axis lengths, and a number of other grain features are stored in a data frame. The distributions of major- and minor grain axis lengths are plotted; they can be weighted by grain areas, so that they are more consistent with grain size distributions that come from sieving, point counting, or Wolman counts (Taylor et al., 2022).

The `Segment_every_grain_w_georeferencing.ipynb` notebook demonstrates how to run Segmenteverygrain on a georeferenced image and save the results as a shapefile. This enables geospatial analyses of the coarse material, capturing variations in grain size across surfaces ([Figure 4](#)).

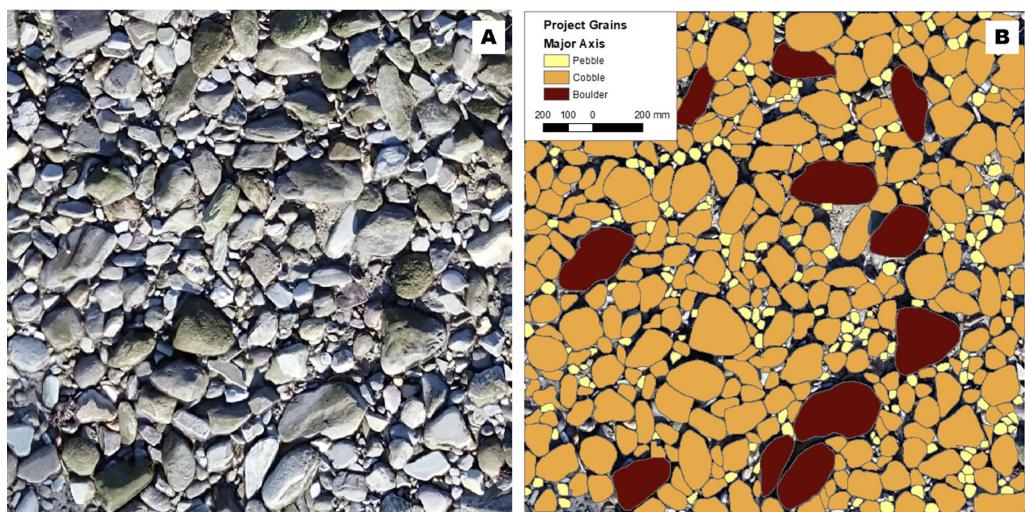


Figure 4: (A) Orthoimagery from ground-based structure-from motion survey of mixed sand and gravel beach. (B) Orthoimagery overlain with segmented grains colored by Wentworth size classes. Data from Roberts (2024).

Dependencies and availability

The Segmenteverygrain package is available from PyPI at <https://pypi.org/project/segmenteverygrain/>. The dependencies include image processing and shape manipulation tools, such as Pillow (Clark, 2015), scikit-image (Van Der Walt et al., 2014), rasterio (Gillies & others, 2013--), and shapely (Gillies et al., 2025). To identify and manipulate overlapping polygons, we rely on the networkx package (Hagberg et al., 2008). The U-Net model is built using tensorflow (Abadi et al., 2015) and keras (Chollet & others, 2015); parts of the ML workflow rely on the scikit-learn library (Pedregosa et al., 2011).

Acknowledgements

Funding was provided by the Quantitative Clastics Laboratory, Bureau of Economic Geology, The University of Texas at Austin. We are thankful to Jake Covault, Sergey Fomel, and Tim Lawton for discussions.

References

- Abadi, M., Agarwal, A., Barham, P., Brevdo, E., Chen, Z., Citro, C., Corrado, G. S., Davis, A., Dean, J., Devin, M., Ghemawat, S., Goodfellow, I., Harp, A., Irving, G., Isard, M., Jia, Y., Jozefowicz, R., Kaiser, L., Kudlur, M., ... Zheng, X. (2015). *TensorFlow: Large-scale machine learning on heterogeneous systems*. <https://www.tensorflow.org/>
- Azzam, F., Blaise, T., & Brigaud, B. (2024). Automated petrographic image analysis by supervised and unsupervised machine learning methods. *Sedimentologika*, 2(2). <https://doi.org/10.57035/journals/sdk.2024.e22.1594>
- Buscombe, D. (2020). SediNet: A configurable deep learning model for mixed qualitative and quantitative optical granulometry. *Earth Surface Processes and Landforms*, 45(3), 638–651. <https://doi.org/10.1002/esp.4760>
- Chen, Z., Scott, C., Keating, D., Clarke, A., Das, J., & Arrowsmith, R. (2023). Quantifying and analysing rock trait distributions of rocky fault scarps using deep learning. *Earth*

- Surface Processes and Landforms*, 48(6), 1234–1250. <https://doi.org/10.1002/esp.5545>
- Chollet, F., & others. (2015). *Keras*. <https://keras.io>.
- Clark, A. (2015). *Pillow (PIL fork) documentation*. readthedocs. <https://pillow.readthedocs.io/en/stable/index.html>
- Gillies, S., & others. (2013--). *Rasterio: Geospatial raster i/o for Python programmers*. Mapbox. <https://github.com/rasterio/rasterio>
- Gillies, S., Wel, C. van der, Van den Bossche, J., Taves, M. W., Arnott, J., Ward, B. C., & others. (2025). *Shapely* (2.1.1). Zenodo. <https://doi.org/10.5281/zenodo.15463269>
- Hagberg, A. A., Schult, D. A., & Swart, P. J. (2008). *Exploring network structure, dynamics, and function using NetworkX*. 11–15. <https://doi.org/10.25080/TCWV9851>
- Kirillov, A., Mintun, E., Ravi, N., Mao, H., Rolland, C., Gustafson, L., Xiao, T., Whitehead, S., Berg, A. C., Lo, W.-Y., Dollár, P., & Girshick, R. (2023). *Segment Anything*. <https://doi.org/10.48550/arXiv.2304.02643>
- Mair, D., Do Prado, A. H., Garefalakis, P., Lechmann, A., Whittaker, A., & Schlunegger, F. (2022). Grain size of fluvial gravel bars from close-range UAV imagery - uncertainty in segmentation-based data. *Earth Surface Dynamics*, 10(5), 953–973. <https://doi.org/10.5194/esurf-10-953-2022>
- Mair, D., Witz, G., Do Prado, A. H., Garefalakis, P., & Schlunegger, F. (2024). Automated detecting, segmenting and measuring of grains in images of fluvial sediments: The potential for large and precise data from specialist deep learning models and transfer learning. *Earth Surface Processes and Landforms*, 49(3), 1099–1116. <https://doi.org/10.1002/esp.5755>
- Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, E. (2011). Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research*, 12, 2825–2830.
- Pielawski, N., & Wählby, C. (2020). Introducing Hann windows for reducing edge-effects in patch-based image segmentation. *PLOS ONE*, 15(3), e0229839. <https://doi.org/10.1371/journal.pone.0229839>
- Prieur, N. C., Amaro, B., Gonzalez, E., Kerner, H., Medvedev, S., Rubanenko, L., Werner, S. C., Xiao, Z., Zastrozhnov, D., & Lapôtre, M. G. A. (2023). Automatic Characterization of Boulders on Planetary Surfaces From High-Resolution Satellite Images. *Journal of Geophysical Research: Planets*, 128(11), e2023JE008013. <https://doi.org/10.1029/2023JE008013>
- Prodanovic, M., Milliken, K. L., & Mehmani, A. (2019). *Offshore Miocene sandstone thin section (Folk McBride collection)*. <https://www.digitalrocksportal.org/projects/244>; Digital Rocks Portal. <https://doi.org/10.17612/rn6g-fq64>
- Purinton, B., & Bookhagen, B. (2021). Tracking Downstream Variability in Large Grain-Size Distributions in the South-Central Andes. *Journal of Geophysical Research: Earth Surface*, 126(8), e2021JF006260. <https://doi.org/10.1029/2021JF006260>
- Ravi, N., Gabeur, V., Hu, Y.-T., Hu, R., Ryali, C., Ma, T., Khedr, H., Rädle, R., Rolland, C., Gustafson, L., Mintun, E., Pan, J., Alwala, K. V., Carion, N., Wu, C.-Y., Girshick, R., Dollár, P., & Feichtenhofer, C. (2024). *SAM 2: Segment anything in images and videos*. arXiv. <https://doi.org/10.48550/arXiv.2408.00714>
- Roberts, K. (2024). *Evaluation of 3d beach profiles: A new method for monitoring changes in beach morphology and grain size* [MS Thesis]. University of Massachusetts Boston.
- Robin, C. Q., Duchene, A., Murdoch, N., Vincent, J.-B., Lucchetti, A., Pajola, M., Ernst, C. M., Daly, R. T., Barnouin, O. S., Raducan, S. D., Michel, P., Hirabayashi, M., Stott, A., Cuervo, G., Jawin, E. R., Trigo-Rodriguez, J. M., Parro, L. M., Sunday, C., Vivet,

- D., ... Chabot, N. L. (2024). Mechanical properties of rubble pile asteroids (Dimorphos, Itokawa, Ryugu, and Bennu) through surface boulder morphological analysis. *Nature Communications*, 15(1), 6203. <https://doi.org/10.1038/s41467-024-50147-w>
- Tang, D. G., Milliken, K. L., & Spikes, K. T. (2020). Machine learning for point counting and segmentation of arenite in thin section. *Marine and Petroleum Geology*, 120, 104518. <https://doi.org/10.1016/j.marpetgeo.2020.104518>
- Taylor, T. R., Lander, R. H., & Bonnell, L. M. (2022). Chapter 6: Quantitative Textural Analysis. In *Sandstone Petrography, Petrology, and Modeling* (pp. 143–160). <https://pubs.geoscienceworld.org/sepm/books/monograph/2359/chapter/133729738/Chapter-6-Quantitative-Textural-Analysis>; SEPM Society for Sedimentary Geology. <https://doi.org/10.2110/sepmcsp.13.06>
- Van Der Walt, S., Schönberger, J. L., Nunez-Iglesias, J., Boulogne, F., Warner, J. D., Yager, N., Gouillart, E., & Yu, T. (2014). Scikit-image: Image processing in Python. *PeerJ*, 2, e453. <https://doi.org/10.7717/peerj.453>