

1 Napari-3D-Counter: A manual cell counter for napari

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Authors of papers retain copyright and release the work under a Creative Commons Attribution 4.0 International License ([CC BY 4.0](#)). 15 Despite the many high-quality automated methods for identifying objects in images, expert annotation is sometimes the most practical option. For example, training and optimizing a machine learning model may require more effort than manual annotation. In these cases, user-friendly software is especially important to save time for the expert annotator. User-friendliness includes both ergonomics (whether the software is intuitive and efficient to use) and stability (whether the software works as expected).

5 Summary

6 A common task across biological fields is to quantify the number of objects in an image. Often, 7 the most efficient solution to this problem is to have an expert manually count those objects. This package, Napari-3D-Counter, includes the Count3D widget, a user-friendly interface to 8 allow an expert to quickly count objects in 2D or 3D images visualized using napari, as well 9 as auxiliary plugins that help to integrate Count3D into upstream and downstream analyses. 10 Napari-3D-Counter focuses on being user-friendly for beginners and experienced users, and has 11 been continually updated since its 2023 release. The package is available on both PyPI and 12 conda-forge, and is indexed on napari-hub. 13

14 Statement of need

15 Despite the many high-quality automated methods for identifying objects in images, expert annotation is sometimes the most practical option. For example, training and optimizing a machine learning model may require more effort than manual annotation. In these cases, user-friendly software is especially important to save time for the expert annotator. User-friendliness includes both ergonomics (whether the software is intuitive and efficient to use) and stability (whether the software works as expected). 20

16 I introduce the package Napari-3D-Counter, which leverages the Python / napari ecosystem to 21 create a user-friendly interface for manual cell counting. Napari is a user-friendly multidimensional image viewer that is open source and implemented in the Python programming language 22 ([Sofroniew et al., 2025](#)). Napari's implementation language gives it the advantage of easily 23 integrating with Python's numerous scientific tools through a plugin system. 24

17 Because napari is under active development, upstream changes can affect plugins. To keep 25 Napari-3D-Counter reliable, fixes are released promptly with the aid of unit tests, which cover 26 over 90% of the code. These tests are automatically run before publication using a GitHub 27 Action. 28

18 The functionality of the main widget provided by Napari-3D-Counter, Count3D, is similar 29 to the FIJI cell counter plugin ([De Vos, 2010](#)), with important differences: no macros are 30 necessary for keyboard automation, locations can be saved in the CSV format instead of XML 31 (enabling easier integration with GUI spreadsheet tools) and most importantly, integration 32 with the Python / napari ecosystem. This integration is significant because napari provides 33 advanced 3D visualization capabilities, while the Python ecosystem offers powerful packages 34 such as scikit-image ([Walt et al., 2014](#)) and SciPy ([Virtanen et al., 2020](#)) for analysis. 35

19 Native napari Points layers can replicate many of the core features of Count3D. However, 36 Count3D has the advantage of being specifically specialized to count cells of different types: it 37 takes one keyboard shortcut to switch between various cell type counters, and there is a live 38 display of how many cells of each type have been counted. Furthermore, saving and loading a 39 single CSV file containing the coordinates of all cells from all types is preferable to creating 40 41

42 separate files for each type. Overall, using Napari-3D-Counter is likely to save the expert
43 annotator's time over using native Napari Points.

44 Finally, Count3D's functionality is also similar to the manual spots feature of Imaris ([Imaris](#),
45 2024). In addition to the ergonomic benefits of a bespoke cell counter listed above, a clear
46 advantage of Count3D over Imaris is its availability under a free software license, while Imaris
47 is proprietary software that requires a costly license.

48 Beyond Count3D's core features, other functions related to manual cell counting are imple-
49 mented in auxiliary plugins: IngressPoints, SplitOnShapes, and ReconstructSelected. Ingress-
50 Points takes a native napari points layer, perhaps created by automated labeling, and turns
51 them into a counted cell type in Count3D. SplitOnShapes splits labels of cell types based
52 on spatial information. For example, if a user wants to quantify the distribution of cells of
53 multiple types across a tissue with multiple repeating segments (eg. spinal cord), they can
54 use a napari Shapes layer to define all the segments in the X and Y axes, and SplitOnShapes
55 will return a count of each cell type within each shape. Finally, ReconstructSelected can be
56 used to aid in visualizing cells: if a user has a Label layer labeling all cells, but they only want
57 to visualize a subset, ReconstructSelected will take those labels containing a Count3D cell
58 and create an image layer containing only those cells, which can then be used to create 2D
59 or 3D images. Overall, these auxiliary plugins help to integrate Count3D into more complex,
60 semi-automated cell counting processes.

61 The utility of this plugin is also reflected in its use. It has been used in scientific publications
62 ([Drake et al., 2025](#); [Sato et al., 2025](#)) and has over 15,000 downloads on conda-forge.

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