In this manuscript, Sitar and Leary present a new set of tools to automate the measurement of zircon axes in polished laser ablation mounts. These freely-available, interactive tools can be locally installed or accessibly run through Google Colab. The authors detail the use of the tools as well as both the deep learning concepts behind the code and limitations users should consider while validating the measurements produced by these tools. First, I would like to state that I do not have expertise in deep learning and cannot speak to the choice of one thresholding method over another, grain-segmenting algorithms, or other technical choices. I am approaching this review as a zircon geochronologist with extensive Chromium experience interested in the user experience and feasibility of integrating the toolset into my workflow.

The authors clearly establish the need to consider grain measurements in detrital studies, and point out a gap in data that could be effectively and efficiently filled with their new toolset. The authors may want to include the 3D grain measurement efforts using MicroCT methods (e.g., Cooperdock et al., 2022; Cooperdock et al., 2019) - these have been applied in the low-temperature thermochronology realm rather than the laser ablation realm, but show the importance of grain size measurements across geochronometric methods. Indeed, manually measuring grains or the application of MicroCT is a time-consuming process, especially as large-n datasets proliferate, and reducing barriers to data collection will facilitate the inclusion of additional dimensions of data. The issue of sectioning bias remains – the authors acknowledge this bias, and are clear about the limitations of this code and need for users to evaluate the data.

The authors make a compelling case for the use of deep learning based techniques to bridge this gap. They acknowledge existing methods of identifying individual grains (ZirconSpotFinder and AnalyZr) and point out how their toolset differs (rapid automated measurements with a reduced need for many hours of user involvement; accessibility through either Jupyter or Google Colab).

I appreciate that the authors utilized training datasets from multiple labs and differing image collection approaches (per-sample mosaic versus image-per-shot). When it comes to the detailed discussion of segmentation techniques and deep learning models, I do not have the background necessary to follow the architectures/backbones or choices in model parameter optimization. I defer to other scientists with expertise in these fields, as the discussion of these matters is described with impenetrable levels of jargon (especially section 3.3). I see a previous reviewer ran into this same situation – the authors have added a glossary at the end of the manuscript, which helps, but does not fully alleviate the difficulty. The point raised in the previous review still stands.
The authors do step through what the toolset is actually doing (section 3.4 and 4, and the inclusion of Figure 2 is very helpful. I chose to run through the Google Colab files and test them for ease of use. I commend the authors on the detailed commentary within the code files and video tutorial! I also really like how they have linked the different notebooks together at the end of each “chapter”. Limitations and warnings about how to produce publication-quality data are included at the relevant points in the code. I did miss the point about playground mode, so in an effort to keep users from inadvertently editing things they should not edit, is it possible to add a cell in the notebook that automatically kicks them over to playground mode? The top of my notebook did read “cannot save changes” as in the tutorial, so maybe this has already been implemented. The notebooks were easy to follow, and are fully suitable for someone with limited programming experience (i.e., students, etc). I tested them on some of my own images and once I structured the project directory appropriately, the code ran without an issue.

Cooperdock et al., 2022: https://gchron.copernicus.org/articles/4/501/2022/
Cooperdock et al., 2019: https://gchron.copernicus.org/articles/1/17/2019/