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Further investigations in Deep Learning for earthquake physics: Analyzing the role of magnitude and location in model performance

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Fault zone properties can evolve significantly during the seismic cycle in response to stress changes, microcracking, and wall rock damage. Distinguishing subtle changes in seismic behavior prior to earthquakes, even in locations with dense seismic networks, is challenging. In our previous works, we applied Deep Learning (DL) techniques to assess alterations in elastic properties before and after large earthquakes. To do that, we used 10,000 seismic events that occurred in a volume around the October 30th 2016, Mw 6.5, Norcia earthquake (Italy), and trained a DL model to classify foreshocks, aftershocks, and time-to-failure (TTF), defined as the elapsed time from the mainshock. Our model exhibited outstanding accuracy, correctly identifying foreshocks and aftershocks with over 90% precision and achieving good results also in time-to-failure multi-class classification.

To build upon our initial findings and enhance our understanding, this follow-up investigation aims to thoroughly examine the model's performance across various parameters. First, we will investigate the influence of earthquake magnitude on our model, specifically assessing whether and to what extent the model's accuracy and reliability are maintained across varying minimum magnitude thresholds included in the catalog. This aspect is crucial to understand whether the model's predictive power remains consistent at different magnitudes of completeness. In terms of source location, our study will extend to evaluate the model's reliability by selectively excluding events from specific locations within the study area, and alternatively, by expanding the selection criteria. This approach allows us to discern the model's sensitivity to spatial variations and its ability to adapt to diverse seismic activity distributions. Furthermore, we'll pay particular attention to the analysis of null-results. This involves meticulously analyzing cases where the model does not perform effectively, producing low-precision or inconclusive results. By carefully examining these scenarios, our goal is to further assess and confirm the high-performance results obtained from previous works.

Our results highlight the promising potential of DL techniques in capturing the details of earthquake preparatory processes, acknowledging that while complexities of machine learning models exist, ML models have the potential to open hidden avenues of future research.