Response to Reviewers

Dear Reviewer,

We appreciate the time and effort that you have dedicated and are grateful for your insightful comments which have improved the manuscript. We have incorporated the constructive suggestions, and have highlighted the changes within the manuscript and marked them in blue color. Here is a point-by-point response to your comments and concerns.

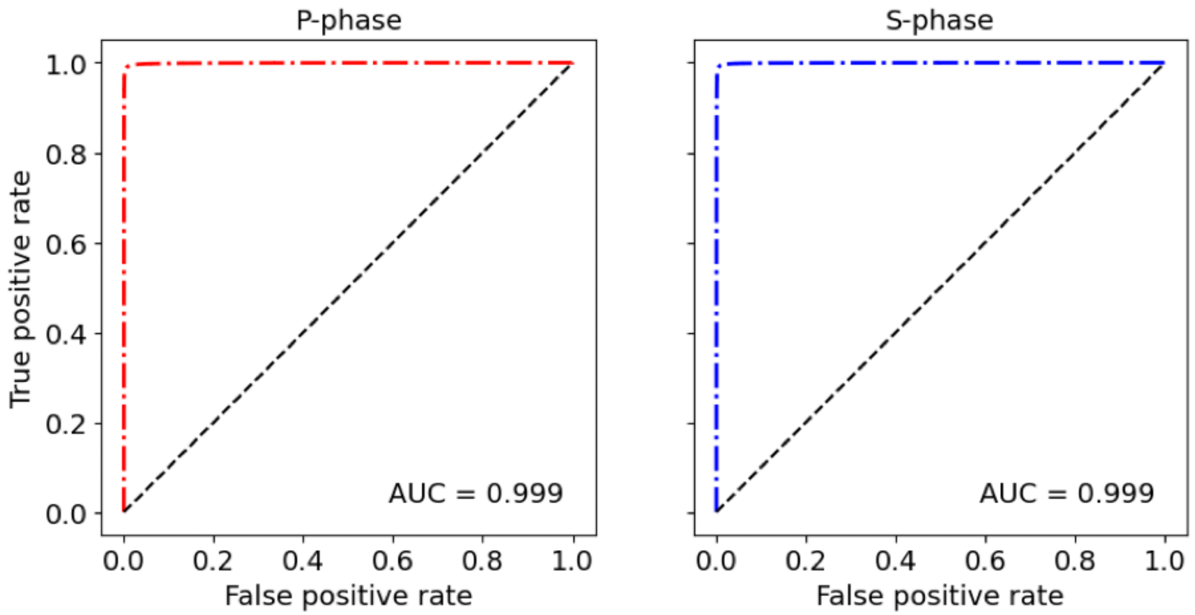
Reviewer 1

In this work, the authors apply the dynamic convolutional neural network to two tasks: seismic phase classification and arrival-time picking. They compared the new model, DynaPicker, to a few other deep learning models and demonstrated that DynaPicker could achieve better performance for input data of different lengths. The main concern I have for this work is that the model comparison may not be very accurate. The reported improvements in precision/recall/F1 scores are not significant, so the performance of DynaPicker may become even worse if choosing a slightly different threshold. Based on the selected examples shown in the paper, the false positive rate of the new model could be very high. I would request the authors to plot precision-recall curves to compare the performance of different models to avoid bias in selecting a specific threshold for comparison. One good example is Münchmeyer et al.'s work of "Which Picker Fits My Data?"

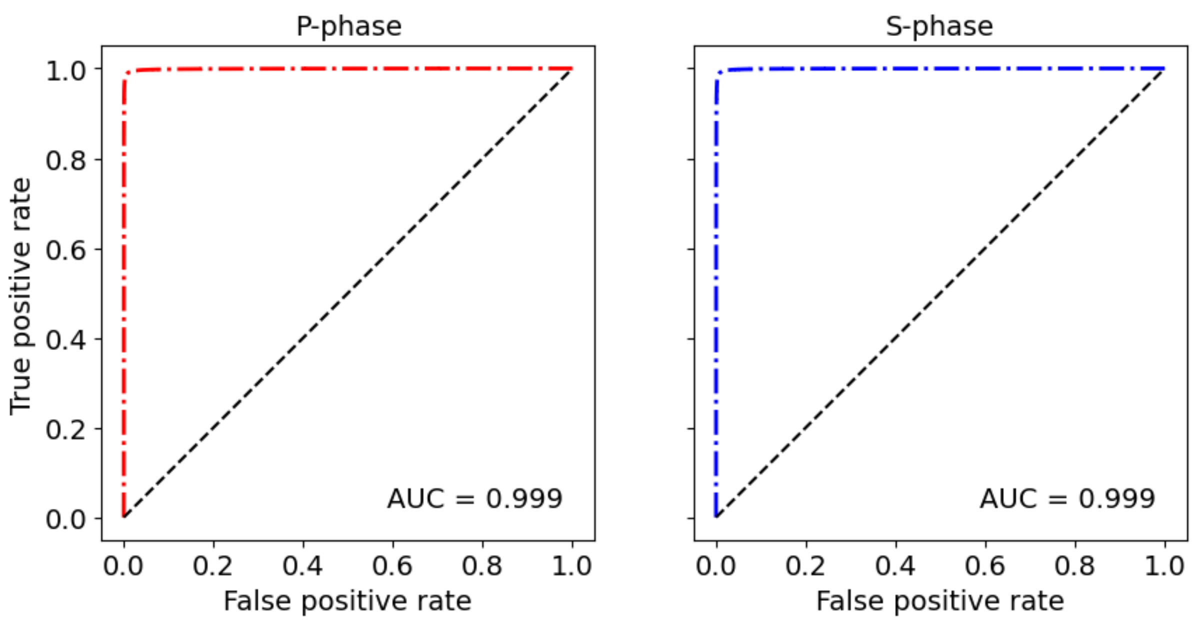
Response: We thank the reviewer for the constructive suggestion.

- Following Münchmeyer et al.'s work "Which Picker Fits My Data?", we have plotted the receiver operating characteristic (ROC) curves for the DynaPicker and GPD models as follows. Based on Figure 1, it's evident that DynaPicker exhibits a similar low false positive rate to the GPD model. Furthermore, the picking error distribution summarized in Tables 4 and 5 that DynaPicker performs better in phase arrival time picking than GPD.
- Unfortunately, even with our multiple attempts, the CapsPhase model retrieved from the git repository cannot be utilized at this time. When loading the CapsPhase model in the created virtual environment, we received a segmentation fault error, even after increasing the memory size. We will keep on trying to perform the comparison with the CapsPhase model and will address this in our follow-up work.

1. Table 4: I have three comments of the reported results: (1) Based on the standard deviations of the time residuals, we can see clearly DynaPicker has a very large time error for both P and S phases. I am wondering if DynaPicker is really an improved



(a) DynaPicker



(b) GPD

Figure 1. ROC curves

alternative to current models. (2) In the table, only the number of picks (< 0.5s) is reported. But how many picks (> 0.5s) does DynaPicker detected? It is important to report the false positives. (3) The absolute number of undetected events is not helpful. What activation threshold do you use? How many false positive events do you detected in order to detect all true events?

Response:

- Here we followed the CapsPhase work definition i.e., 'if the error between the model's predicted picks and the ground truth picks have an absolute error below 0.5s, then it is true positive'. As indicated in Table 4, the time residuals of DynaPicker exhibit standard deviations that are either similar to or smaller than those of other models. In certain instances, DynaPicker even surpasses the other models by having lower standard deviations.
- In Table 4, a total number of 10,000 events for each scenario are randomly selected from the STEAD dataset. All of these earthquake events are correctly detected using DynaPicker. In case 1 (used model: DynaPicker), there are 945 events with P-phase picking errors exceeding 0.5s and 2304 events with S-phase picking errors exceeding 0.5s, respectively. In case 2 (used model: GPD), there are 2595 events with P-phase picking error and 2403 events with S-phase picking error greater than 0.5s, respectively. In both Tables 4 and 5, we have introduced two additional columns to denote the number of picks exceeding 0.5s for both P- and S-phases as shown in the following tables.
- In the task of the seismic phase classification with the SCEDC dataset, we did not use any activation threshold for event detection. However, in the context of analyzing the aftershock sequence of the Turkey earthquake, we empirically established an activation threshold of 0.7 for detecting events. We would further like to point out that the threshold should indeed be chosen carefully by the user based on the station and the data and what we show here is an example. The threshold of 0.7 was chosen experimentally to get the most optimum balance between false positives and false negatives.

Changes in manuscript: We have updated Tables 4 and 5 in the manuscript. Line 78-80 are added

2. Fig. 2: I am confused by this plot. If the predicted scores are also pretty high for waveforms that are not P or S phases, there could be many false positives. Based on the examples shown in Fig. 5, we can see DynaPicker can also easily pick up false positives.

Response: Figure 2 provides a schematic representation of the arrival time picking process for continuous seismic data, employing various window sizes while processing the same continuous waveform. Even though the probability might be relatively high (> 0.7) in few other windows, we opt for the window with the highest P/S probability, which usually is in the order of 0.99, to estimate the phase arrival time. As illustrated in the initial ROC curves, by following this approach, DynaPicker exhibits a minimal number of false positives.

3. Eq. 5: Did you compare the results using T = 1 and T = 4 for the phase picking problem? Because the temperature softmax function is not used by previous works of phase picking, it is necessary to demonstrate that it can help the phase picking task.

Response: We concur with this observation of the reviewer. We have summarized the outcomes of utilizing different temperatures for phase picking in the Appendix. The relevant table is presented below. You can find this table on page 22 of the

Table 4. Body-wave arrival time evaluation using different methods on STEAD dataset including (a) $S_{arrival} - P_{arrival} > 4$s and (b) $S_{arrival} - P_{arrival} < 4$s. In each case, 1×10^4 samples are used. Same as the CapsPhase paper, the event whose pick predicted by a model has an absolute error larger than 0.5 s, is recognized as false positive.

(a) $S_{arrival} - P_{arrival} > 4s$

Method	No. of events detected	No. of abs(e) ≤ 0.5s for P-pick	μ_P	σ_P	No. of abs(e) > 0.5s for P-pick	No. of abs(e) ≤ 0.5s for S-pick	μ_S	σ_S	No. of abs(e) > 0.5s for S-pick
DynaPicker	10000	**9055**	**0.0002**	0.151	945	**7696**	**0.011**	0.203	2304
GPD	9826	8975	-0.0036	0.149	851	2623	-0.043	0.193	7203
CapsPhase	9885	8766	-0.018	0.149	1119	5545	-0.112	0.184	4340
AR picker	10000	7963	0.079	0.133	2037	4011	0.205	0.176	5989

(b) $S_{arrival} - P_{arrival} < 4s$

Method	No. of events detected	No. of abs(e) ≤ 0.5s for P-pick	μ_P	σ_P	No. of abs(e) > 0.5s for P-pick	No. of abs(e) ≤ 0.5s for S-pick	μ_S	σ_S	No. of abs(e) > 0.5s for S-pick
DynaPicker	10000	**9405**	**0.0048**	0.091	595	**7597**	**0.0075**	0.179	2403
GPD	9662	8890	0.0059	0.092	772	4393	-0.012	0.164	5269
CapsPhase	9861	8767	-0.020	0.084	1094	5545	-0.061	0.164	4316
AR picker	10000	7755	0.015	0.075	2245	7369	0.126	0.161	2361

μ_P and σ_P are the mean and standard deviation of errors (ground truth − prediction) in seconds respectively for P phase picking. μ_S and σ_S are the mean and standard deviation of errors (ground truth − prediction) in seconds respectively for S phase picking.

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4. L230: "we can observe that EPick achieves the best performance in phase picking over DynaPicker by using different window sizes." Does this mean the claimed advantage of DynaPicker for different input length is not true? Although you explain that the reason is that EPick is pre-trained using the STEAD dataset, you can also train DynaPicker using the STEAD dataset to make the comparison more accurate.

Response: In response to the reviewer's recommendation, we proceeded to retrain the EPick model using the same dataset sourced from the STEAD data, which serves as the training data for DynaPicker. Subsequently, we employed the retrained EPick model to estimate phase arrival times for continuous data extracted from the STEAD dataset. It is important to highlight that there is no overlap between the datasets used for EPick training and those utilized for phase arrival time detection. We observed that, while the performance in detecting the P phase was similar, the accuracy of S-Phase picking decreased from a mean value of -0.002s to -0.050s, and the standard deviation increased from 0.122s to 0.147s. Additionally, The EPick model is developed for the task of estimating seismic phase arrival times with fixed input length. In contrast, the DynaPicker model

Table 5. Body-wave arrival time evaluation using different methods on INSTANCE dataset including (a) $S_{arrival} - P_{arrival} > 4$s and (b) $S_{arrival} - P_{arrival} < 4$s. In each case, 1×10^4 samples are used. Same as the CapsPhase paper, the event whose pick predicted by a model has an absolute error larger than 0.5 s, is recognized as false positive.

(a) $S_{arrival} - P_{arrival} > 4s$

Method	No. of events detected	No. of abs(e) ≤ 0.5s for P-pick	μ_P	σ_P	No. of abs(e) > 0.5s for P-pick	No. of abs(e) ≤ 0.5s for S-pick	μ_S	σ_S	No. of abs(e) > 0.5s for S-pick
DynaPicker	10000	**8707**	0.030	0.130	1293	**7530**	**0.019**	0.199	2470
GPD	9623	8231	0.028	0.123	1392	4726	-0.032	0.179	4897
CapsPhase	9598	7948	0.014	0.140	1650	5837	-0.103	0.186	3761
AR picker	9999	7545	0.052	0.118	2454	3274	0.218	0.168	6725

(b) $S_{arrival} - P_{arrival} < 4s$

Method	No. of events detected	No. of abs(e) ≤ 0.5s for P-pick	μ_P	σ_P	No. of abs(e) > 0.5s for P-pick	No. of abs(e) ≤ 0.5s for S-pick	μ_S	σ_S	No. of abs(e) > 0.5s for S-pick
DynaPicker	10000	**8690**	**0.012**	0.079	1310	**7815**	**0.0085**	0.160	2185
GPD	9833	8109	0.022	0.075	1724	6647	-0.019	0.134	3186
CapsPhase	9872	7984	0.019	0.091	1888	5447	-0.072	0.143	4325
AR picker	10000	8296	0.016	0.077	1704	5778	0.149	0.168	4222

μ_P and σ_P are the mean and standard deviation of errors (ground truth − prediction) in seconds respectively for P phase picking. μ_S and σ_S are the mean and standard deviation of errors (ground truth − prediction) in seconds respectively for S phase picking.

Table A1. Body-wave arrival time evaluation using different temperatures on the STEAD dataset.

T	No. of undetected events	No. of abs(e) ≤ 0.5s for P-pick	μ_P	σ_P	No. of abs(e) ≤ 0.5s for S-pick	μ_S	σ_S
1	0	8926	0.018	0.132	7168	-0.003	0.199
4	0	9032	0.005	0.125	6984	0.002	0.196
10	0	9063	0.0008	0.123	6857	0.004	0.196
20	0	9084	-0.001	0.122	6797	0.004	0.196

μ_P and σ_P are the mean and standard deviation of errors (ground truth − prediction) in seconds respectively for P phase picking. μ_S and σ_S are the mean and standard deviation of errors (ground truth − prediction) in seconds respectively for S phase picking.

was primarily designed for phase classification and its adaptation for phase arrival time detection with different input lengths is a notable application. Furthermore, as the size of the training data increased, DynaPicker exhibited improved performance and demonstrated greater robustness when compared to EPick.

Changes in manuscript: Texts updated to help readers understand the process on pages 11 and 12.

5. L240: "The testing accuracy of DynaPicker is 98.82%, which is slightly greater than CapsPhase [30] (98.66%) and 1D-ResNet [9] (98.66%)." Because the differences are very small and do not tell readers much information, could you compare the waveforms of false predictions of these models to help understand where DynaPicker can be better?

Response: As per reviewer's suggestion, here, we plot several waveforms of false predictions, while they are correctly identified by DynaPicker.

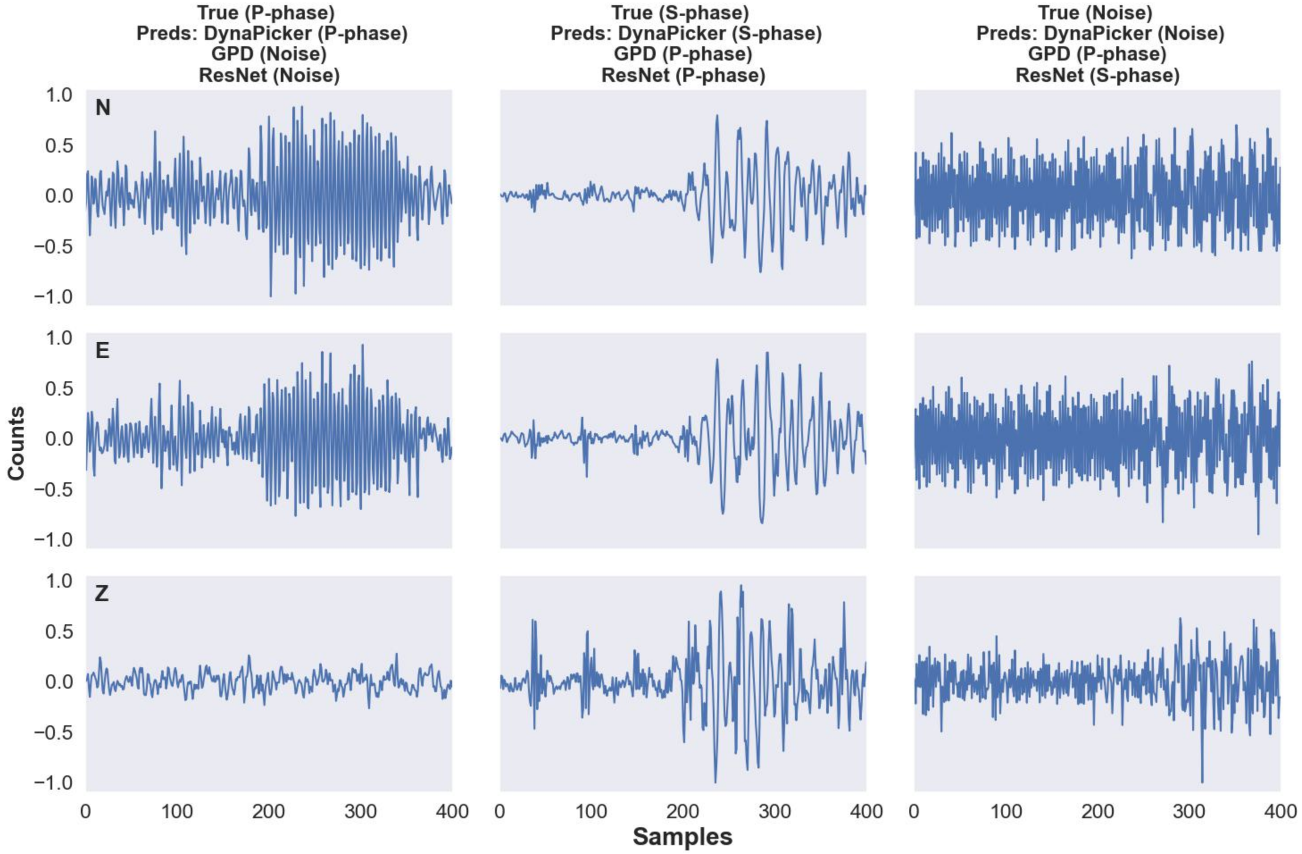

Figure 2. Visualization of trace examples.

From these figures, we can observe that compared with other models, DynaPicker shows its advantage in phase classification. in scenarios where the ground truth label is noise and the seismic waveform exhibits increased noise levels, DynaPicker accurately identifies it as noise, whereas the GPD and ResNet models tend to misclassify it. Unfortunately, as mentioned before, the CapsPhase model retrieved from the git repository cannot be utilized at this time.