

Japan Earthquake Detection and Analysis using Convolutional Neural Network

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Introduction

- The solutions from authors to mitigate the earthquake damage: automatic earthquake monitoring and catalog updating.
- One of previous researches is using convolutional neural network (CNN) to automatically pick seismic phases in waveforms (Ross et al, 2018).
- The problem: mentioned research is not yet tested on Japan's MeSO-net data, which is contaminated with artificial noise.
- This research's objective: **to test and enhance the performance of CNN model in noise-contaminated MeSO-net waveforms**

Data

Training data:

- 4.5 millions velocity waveforms, divided equally among P-wave, S-wave, noise (obtained from pre-event noise) from Southern California Seismic Network catalog.
- 4 s (400 samples) in duration
- Detrended and high-pass filtered above 2 Hz, and were resampled at 100 Hz.
- Labeling to classify each wave type is based on pattern of each waves that is determined by numbers (0 = P-wave, 1 = S-wave, 2 = noise).

Japan earthquake data:

- MeSO-net acceleration waveform from 10 events, 3 stations (IIDM, TACM, and TK2M) each (sampling frequency 200 Hz).

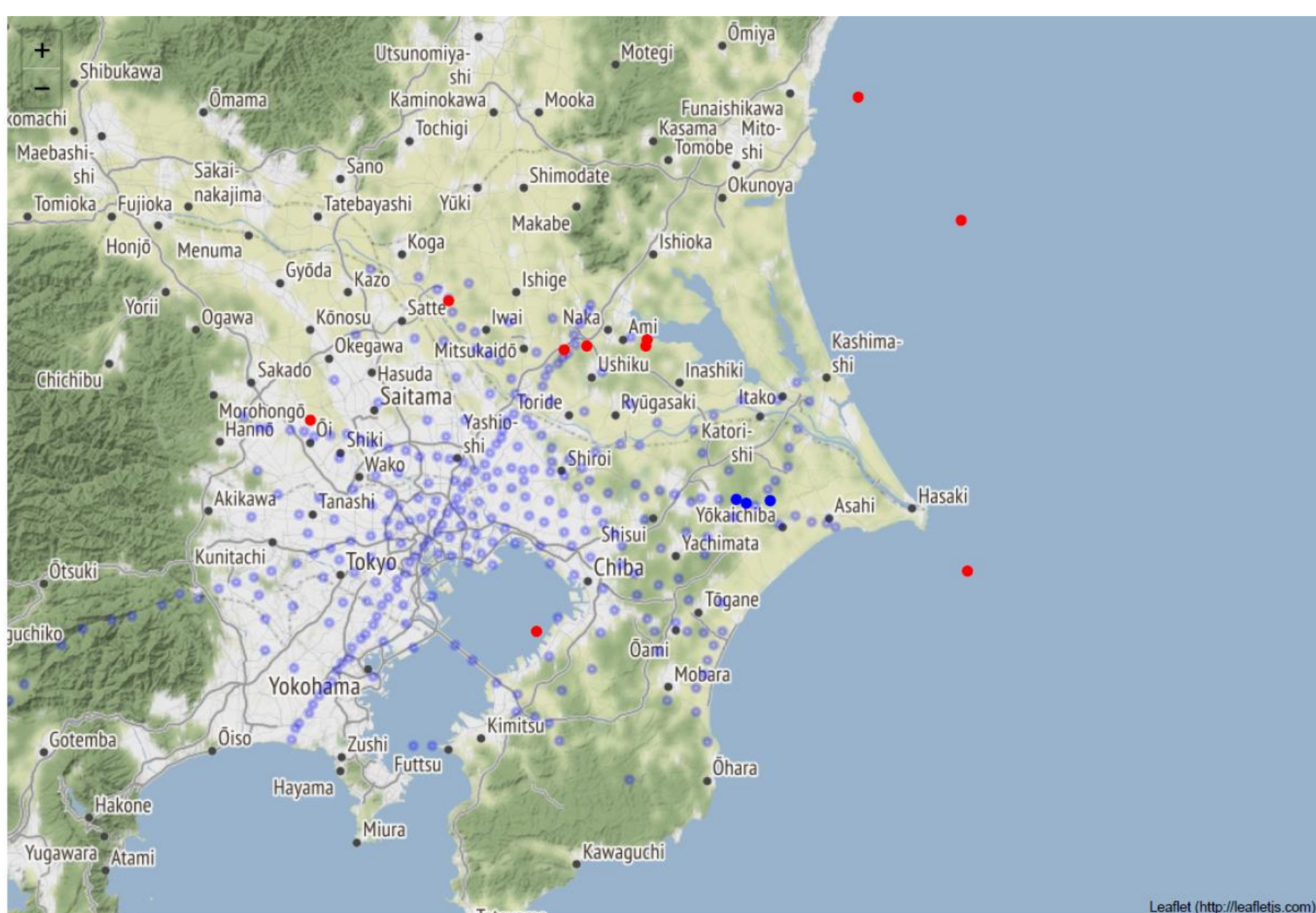


Figure 1. Location of the stations (dark blue dots) and hypocenters (red dots) of MeSO-net Data.

Methods

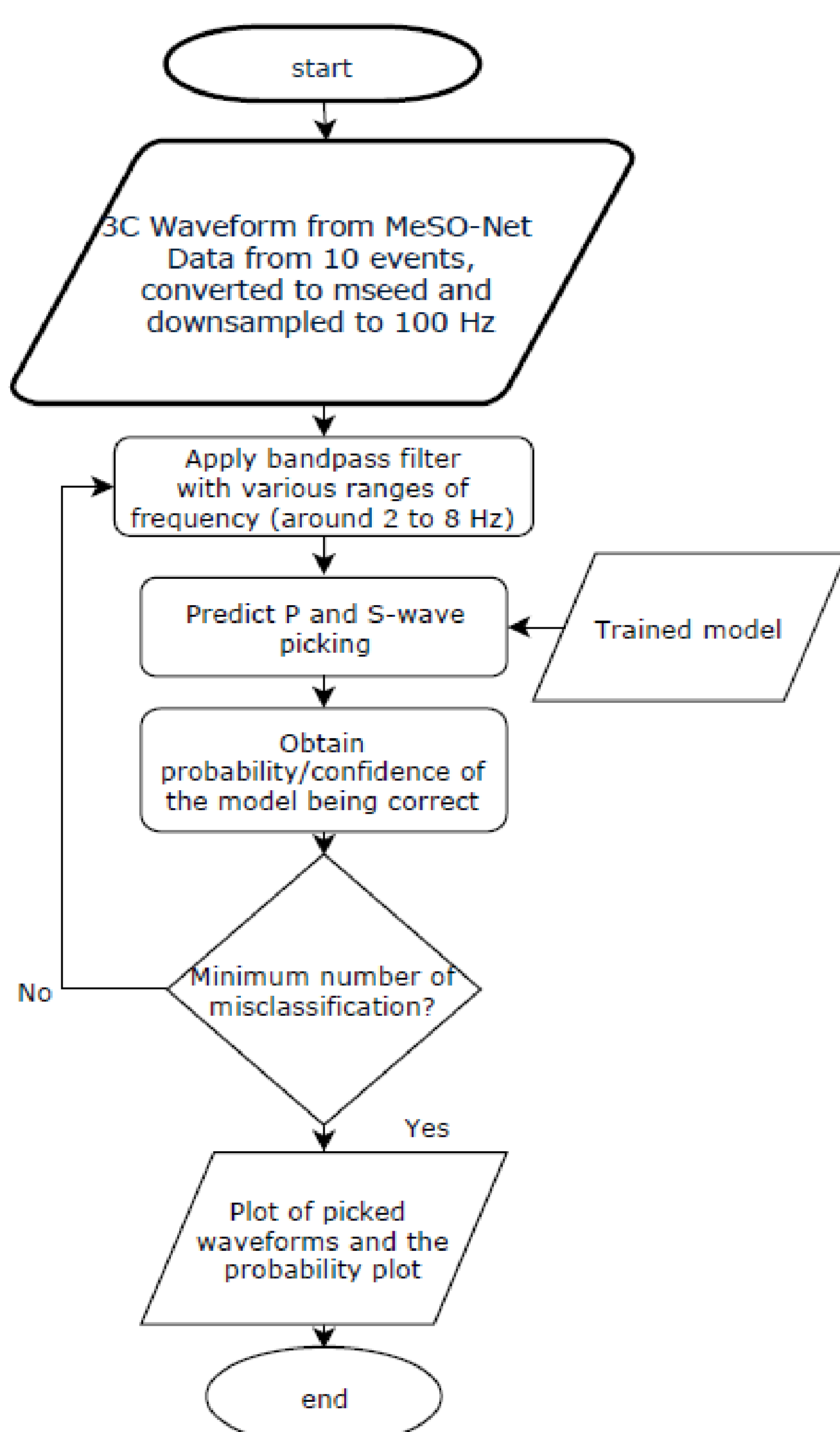


Figure 2. Flowchart of how the MeSO-net data is analyzed using the CNN model.

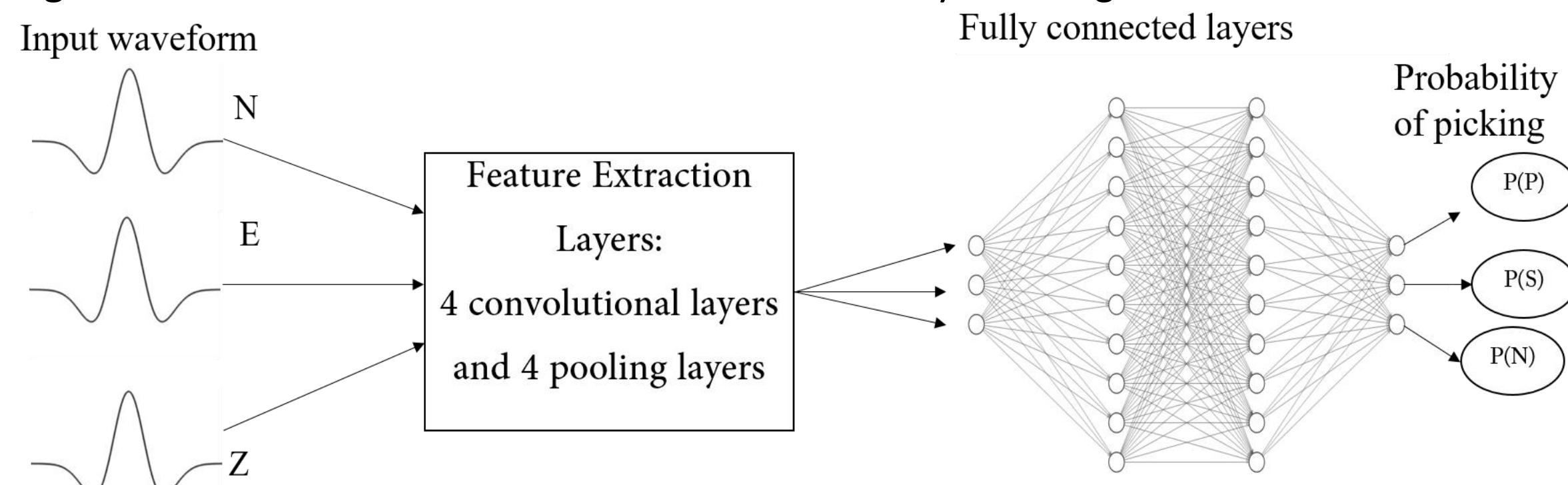


Figure 3. CNN architecture for training the model (Ross et al, 2018).

Acknowledgement

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Results

The output (30 plots) each contains picks on 3 components waveform and probability (confidence that the picked data match with the features learned) value of the picking.

Left to right: IIDM, TACM, TK2M station

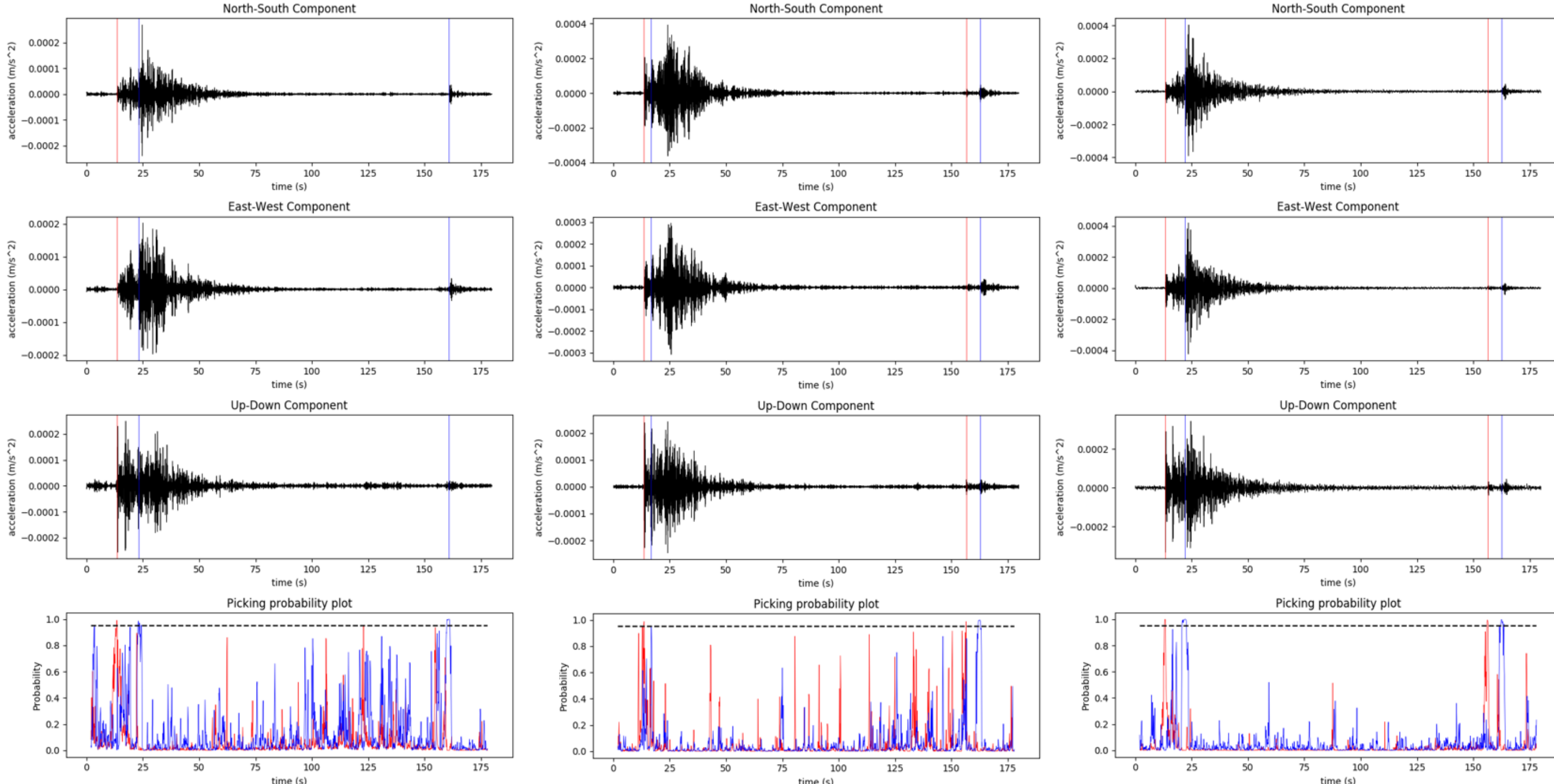


Figure 4. Example of correctly picked seismograms by CNN model from 3 stations with probability plots. Notice the small earthquakes swarms can also be detected. Red vertical line indicates incoming P-wave, while blue line indicates incoming S-wave. The threshold probability is 0.95.

Table 1. Comparison between wave arrival time picking by CNN model and manual picking that had been done before in IIDM (a), TACM (b), and TK2M (c) station corresponding to Figure 4. CNN model can detect earthquake swarms after the major events.

| (a) | | | (b) | | | (c) | | |
|----------|-------------------------|----------------------|----------|-------------------------|----------------------|----------|-------------------------|----------------------|
| | Manual picking time (s) | CNN picking time (s) | | Manual picking time (s) | CNN picking time (s) | | Manual picking time (s) | CNN picking time (s) |
| First P | 13.8 | 13.4 | First P | 13.4 | 13.6 | First P | 13.2 | 13.2 |
| First S | 23.21 | 23 | First S | 22.53 | 16.2 | First S | 22.16 | 22 |
| Second P | - | - | Second P | - | 156.6 | Second P | - | 156.3 |
| Second S | - | 160.9 | Second S | - | 161.7 | Second S | - | 162.5 |

Table 2. Confusion matrix that measures the performance of model. The numbers are counted from the amount of picking on all events.

- Precision P** = $32/(32+0+0) = 32/32 = 1$
- Precision S** = $31/(31+0+8) = 31/39 = 0.79$
- Recall P** = $32/(32+0+1) = 32/33 = 0.97$
- Recall S** = $31/31 = 1$

| | True P | True S | True Noise |
|-----------------|--------|--------|------------|
| Predicted P | 32 | 0 | 0 |
| Predicted S | 0 | 31 | 8 |
| Predicted Noise | 1 | 0 | |

Discussion

- Major earthquakes were successfully detected with this CNN model and the time at which the events were detected proved to be accurate overall.
- Several different filters did not eliminate some false positives
- Main cause: other type of noises such as noise from traffic are not available in large quantity in the training data set.
- Mislabel because model does not know noise type in MeSO-net data
- Experimented with frequency range for bandpass filter to optimally cut out the noise as much as possible.
- After careful filtering by analyzing the noise frequency range with spectral analysis, the precision and recall score increases significantly that the model is able to give reliable predictions.

Conclusions

- Major earthquake events automatic detection from MeSO-net data were successfully done by the CNN. It could also detect earthquake swarms.
- Signal processing, especially frequency range for the filter, is important prior to feeding the waveform to the model. The most reliable frequency range for bandpass filter in our experiment was 2.5 Hz to 6 Hz.
- Train with wide variety of noise to improve its model performance.
- This CNN can prove to be useful as a tool for earthquake monitoring and earthquake catalog generation.

Recommendations

- Include waveforms with artificial noise to the training data so the noise can be distinguished more accurately.
- Improve the CNN model to be more efficient when used in less-sophisticated computer hardware to democratize AI in geoscience.
- Apply CNN to automatically detect earthquakes in Indonesia (no researches about it has been done)

References

Ross, Z. E., Meier, M.A., Hauksson, E., & Heaton, T. H. (2018). Generalized seismic phase detection with deep learning. *Bulletin of the Seismological Society of America*, 108(5A), 2894–2901.