

Deep Neural Network-based minimum temperature prediction for orchards in Yamagata prefecture

*Koyo Kojima¹, Mizuo Kajino², Okuno Takashi³

1. University of Tsukuba, 2. Meteorological Research Institute, 3. Yamagata University

Yamagata Prefecture is known as one of the most famous fruit tree production areas in Japan. However, fruit trees can suffer from freezing and frost damage due to low temperatures in early spring. In April 2021, cold air inflow and radiative cooling damaged 4,181ha of crops in the prefecture, resulting in losses of approximately 12.9-billion-yen¹. There are several methods to prevent frost damage, but because of the high cost of these methods, accurate temperature prediction is essential for efficient operation. The Japan Meteorological Agency provides 39-hour temperature forecasts using the Meso-Scale Model (MSM), allowing predictions of nighttime temperatures up to two days in advance. However, the spatial and temporal resolution of MSM is relatively coarse, making it difficult to accurately predict local temperature variations influenced by orchard topography and soil conditions. Additionally, frost risk maps¹ based on interviews are expected to provide climatological explanations to further improve the accuracy of frost damage prediction.

Therefore, this study aims to predict minimum temperatures in the orchards of Kaminoyama City, Yamagata Prefecture, using deep learning, to evaluate its accuracy, and to clarify the climatological factors contributing to low temperatures in the orchards.

Deep Neural Network (DNN) was adopted as the deep learning model. Compared to traditional machine learning, DNN offers higher accuracy and feature extraction capabilities and is widely applied in fields such as image recognition, speech recognition, and natural language processing. For model verification and training, we used observational data from Kaminoyama City orchards, provided as part of Yamagata University's "Karuhoku Future Creation Lab"². We extracted features from MSM data—including temperature, wind direction/speed, relative humidity, pressure, and time—and input into the DNN along with the observational data. The training period was April 2021-2023, and the test period was April 2024. To evaluate the DNN and verify its prediction accuracy, we used Mean Squared Error (MSE) and Root Mean Squared Error (RMSE).

The figure shows correction results for daily minimum temperatures at Aioi orchard in Kaminoyama City during April 2024. While MSM's RMSE was 3.5°C, using DNN showed an improvement of approximately 1.5°C. The SHAP values after training showed west-southwesterly winds and time contributed most to accuracy improvement after temperature (figure omitted). This indicates the possibility of clarifying the cause of the temperature decrease.

In the future, we plan to compare the prediction results of DNN with those of machine learning models to verify the usefulness of DNN for low-temperature predictions. Additionally, we will examine wind direction, speed, and temporal patterns during low-temperature events to better understand the causes of low-temperature in Kaminoyama City orchards.

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1: Yamagata Prefecture Department of Agriculture, Forestry and Fisheries, 2022. *Fruit Tree Frost Damage Countermeasure Manual* | <https://www.pref.yamagata.jp/documents/21970/houkoku04.pdf>, Accessed: February 14, 2025.

2: *Karuhoku Future Creation Lab - Yamagata City* |

https://sdgs.yamagata-u.ac.jp/project/detail_251.html, Accessed: February 14, 2025.

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