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A review of deep learning used in the hyperspectral image analysis for agriculture

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Abstract

Hyperspectral imaging is a non-destructive, nonpolluting, and fast technology, which can capture up to several hundred images of different wavelengths and offer relevant spectral signatures. Hyperspectral imaging technology has achieved breakthroughs in the acquisition of agricultural information and the detection of external or internal quality attributes of the agricultural product. Deep learning techniques have boosted the performance of hyperspectral image analysis. Compared with traditional machine learning, deep learning architectures exploit both spatial and spectral information of hyperspectral image analysis. To scrutinize thoroughly the current efforts, provide insights, and identify potential research directions on deep learning for hyperspectral image analysis in agriculture, this paper presents a systematic and comprehensive review. Firstly, its applications in agriculture are summarized, include ripeness and component prediction, different classification themes, and plant disease detection. Then, the recent achievements are reviewed in hyperspectral image analysis from the aspects of the deep learning models and the feature networks. Finally, the existing challenges of hyperspectral image analysis based on deep learning are summarized and the prospects of future works are put forward.

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Ethics declarations

Conflict of interest

The authors declare that they have no conflict of interest.

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