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3D Convolutional Neural Networks for Crop Classification with Multi-Temporal Remote Sensing Images

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Abstract: This study describes a novel three-dimensional (3D) convolutional neural networks (CNN) based method that automatically classifies crops from spatio-temporal remote sensing images. First, 3D kernel is designed according to the structure of multi-spectral multi-temporal remote sensing data. Secondly, the 3D CNN framework with fine-tuned parameters is designed for training 3D crop samples and learning spatio-temporal discriminative representations, with the full crop growth cycles being preserved. In addition, we introduce an active learning strategy to the CNN model to improve labelling accuracy up to a required threshold with the most efficiency. Finally, experiments are carried out to test the advantage of the 3D CNN, in comparison to the two-dimensional (2D) CNN and other conventional methods. Our experiments show that the 3D CNN is especially suitable in characterizing the dynamics of crop growth and outperformed the other mainstream methods.

Keywords: 3D convolution; convolutional neural networks; crop classification; multi-temporal remote sensing images; active learning

1. Introduction

Benefiting from the huge number of high-quality spectral-temporal images captured from Earth observation satellites, or unmanned aerial vehicles (UAV), automatic crop classification [1,2] is becoming a fundamental technology for yield estimation, economic assessment, crop transportation, etc. Conventional classification methods, such as support vector machine (SVM) [3], K-nearest neighbor (KNN) [4], maximum likelihood classification (MLC) [5], etc., have been successfully applied in crop classification. However, these methods may be insufficient under the circumstances vegetation, etc. For example, many agricultural sectors of Chinese local governments are doing heavy manual labelling work to assure accurate reports. Therefore, it is still very important to develop new crop classification technologies.

Classification methods in remote sensing mainly consider two aspects, a feature extractor that transforms spatial, spectral, and/or temporal data into discriminative feature vectors, and a classifier that labels each feature vector to certain types. For crop or vegetation classification, the spatial and spectral features are typically extracted in two ways. One is to aggregate spectral bands into vegetation indices that represent the physical characteristics of vegetation, within which the normalized difference vegetation index (NDVI) is mostly used. Wardlow et al. analyzed the time-series MODIS 250 m enhanced vegetation index (EVI) and NDVI datasets for crop classification [1]. Xiao et al. utilized NDVI,