Abstract

This paper presented a state-of-the-art framework, Time Gated Convolutional Neural Network (TGCNN) that takes advantage of temporal information and gating mechanisms for the crop classification problem. Besides, several vegetation indices were constructed to expand dimensions of input data to take advantage of spectral information. Both spatial (channel-wise) and temporal (step-wise) correlation are considered in TGCNN. Specifically, our preliminary analysis indicates that step-wise information is of greater importance in this data set. Lastly, the gating mechanism helps capture high-order relationship. Our TGCNN solution achieves $0.973$ F1 score, $0.977$ AUC ROC and $0.948$ IoU, respectively. In addition, it outperforms three other benchmarks in different local tasks (Kenya, Brazil and Togo). Overall, our experiments demonstrate that TGCNN is advantageous in this earth observation time series classification task.

1. Introduction

Satellite earth observation (EO) data has been widely used in various domains including urban management, climate change, agriculture, environmental monitoring [1, 3, 13, 18], etc. The recent advances in both EO technology and artificial intelligence community have gathered attentions in applying machine learning techniques to EO data with spatial, spectral and temporal characteristics. One of the most prominent machine learning approaches is supervised machine learning. As often noted by researchers, the availability of high-quality data is of great importance to the performance of a classification system. It is critical to have large number of training data to establish a deep learning model such as Convolutional Neural Networks (CNN) suitable for global generalization.

When it comes to time series problems, the EO data usually has two spatial dimensions (width and height of channels), one spectral dimension (number of bands) and temporal dimension (e.g. time step). Existing studies proposed various deep learning frameworks to solve these challenges [4,8–11], but the approach of dealing with such complex space into a feature space with relevant information is crucial. For instance, Tseng et al. took the advantage of meta learning and achieved satisfying results on local tasks while training with a global data set [15,16]. Model Agnostic Meta Learning (MAML) is compatible with any model trained with gradient descent and applicable to classification tasks [5]. In our study, we also considered MAML as a benchmark for comparison.

On the CropHarvest challenge track, the released data is spatially and semantically comprehensive, consisting of more than 90,000 samples with crop/non-crop and agricultural class labels collected from various sources covering 343 labels [16]. The input variables cover multiple modes containing Sentinel-1 synthetic aperture radar information, Sentinel-2 multispectral information, ERA5 climatological variables, SRTM DEM topographic variables, etc. Such a unique and global data set offers new opportunities for research and a variety of applications as well as new challenges.

2. Methodology

2.1. Feature engineering

In the CropHarvest data set, one of the input variables is normalized difference vegetation index (NDVI), calculated by using NIR (near-infrared, wavelength 835 nm) and R (Red, wavelength 665 nm) bands, because vegetation generally absorbs red and reflects NIR spectral information [16]. Among various types of vegetation indices, NDVI is among the most frequently used. However, in high vegetation covered areas, NDVI may be saturated, in addition to its non-linear relationship with bio-physiological
Vegetation index | Abbreviation | Calculation |
|----------------|-------------|-------------|
| Normalized Difference Vegetation Index | NDVI | $\frac{NIR - R}{NIR + R}$ |
| Soil Adjusted Vegetation Index | SAVI | $\frac{NIR - R}{NIR + R + L} \times (1 + L)$ |
| Simple Ratio Index | SR | $\frac{NIR}{R}$ |
| Red-Edge Chlorophyll Index (RECI) | RECI | $\frac{NIR}{R} - 1$ |
| Normalized Difference Red Edge Index | NDRE | $\frac{NIR - R}{NIR + R}$ |
| Modified Soil Adjusted Vegetation Index | MSAVI | $\frac{2 \times NIR + 1 - \sqrt{(2 \times NIR + 1)^2 - 8 \times (NIR - R)}}{2}$ |
| Normalized Difference Water Index | NDWI | $\frac{G - NIR}{NIR + G}$ |
| Green Chlorophyll Index | GCI | $\frac{NIR}{G} - 1$ |

Table 1. Constructed vegetation indices

variations. Inclusion of more vegetation indices could be beneficial. Thus, we constructed several more indices as additions to the input variables that also involve G (green, wavelength 560 nm) and RE (red edge, wavelength 740 nm) bands. These vegetation indices are soil adjusted vegetation index (SAVI), simple ratio index (SR), red edge chlorophyll (RECI), normalized difference red edge index (NDRE), modified soil adjusted vegetation index (MSAVI), normalized difference water index (NDWI) and green chlorophyll index (GCI) [2, 6, 7, 12, 14, 17], as shown in Tab. 1.

2.2. Architecture overview of TGCNN

Here we propose a novel Time Gated Convolutional Neural Network (TGCNN) framework for time series classification, as illustrated in Fig. 1. The framework incorporates the gating mechanism while temporal information is processed and converted into a different feature map, hence the name TGCNN. Firstly, most input variables of the input data are fed into 2D convolutional filters while temporal information goes through 1D convolutional filters, which will yield two feature maps. This guarantees that temporal information is fully integrated to discriminate between the target classes.

In Fig. 1, the upper light blue section indicates processing explanatory variables through a 2D convolutional filter, converted to feature map to reduce dimensionality with a $1 \times 1$ convolutional filter. The convolutional block consists of a 2D convolutional layer, an instance normalization layer and a ReLU activation layer. Instance normalization proves to be beneficial to improve training convergence and reduce the sensitivity to network hyperparameters as a mini-batch of data is normalized for each observation independently. The ReLU activation layer provides the nonlinearity here. Window size refers to the time window size acting as a hyperparameter, i.e. window size x1 means each explanatory variable is considered to extract discriminative features. Similarly, the middle section mirrors the explanatory variables except that for temporal information, 2D convolutional layers are replaced with 1D ones. Then the spatial (channel-wise) and temporal (step-wise) feature maps are concatenated, processed with another 1D convolutional filter and processed with the next gating module.

In recent years, Transformer has emerged as state-of-the-arts in various domains, including time-series challenges [10, 11]. Along with the success of Transformer, some studies sought further development in CNN and proposed to utilize tokenization and embedding process at the stem as an alternative of convolution [4, 9]. Inspired by these works, the lower gating module in Fig. 1 consists of N blocks with identical structures, each resembling a Gated Linear Units (GLU). We find it efficient to adopt this self-attention-like gating structure for its simplicity. Its computation cost is linear over the input channel size and quadratic over the time series length. Note that after the GeLU activation layer, the features are split into two parts along the channel dimension to take advantage of gating and multiplicative function.

2.3. Performance tricks

For the final activation layer, the tanh nonlinearity restricts the rate of change of the hidden state in order to avoid large initial losses, which proves to be beneficial in this gating module. This may be similar to RNNs where the amount of change between time steps are constrained.

Since the discriminant information such as spatial (channel-wise) and temporal (step-wise) variables are crucial in multivariate time series problems, we performed analysis on explicitly extracting spatial features alone and temporal features alone. The step-wise features indicated higher importance. This also echoes the benefits of separately processing variables related to temporal information.
3. Analysis Results

The number of dimensions of original data set has expanded with additional vegetation indices corresponding to Tab. 1. These feature engineering were mainly constructed using Sentinel-2 multispectral information and applied to both training and test data. We assessed the performance of our model by comparing with Gated Transformer [10], and benchmarks from [16] with two different setups (Random weights and MAML initiation, respectively).

As Fig. 2 demonstrates, it only takes approximately 20 epochs for our TGCNN model to ascend to a desired level for the Brazil task, significantly outperforming the other three models. As for the Kenya and Togo tasks, all models are showing comparable performances. In addition, F1 score performances on CropHarvest test data of the four different model settings are evaluated and presented in Tab. 2. One can conclude that our model outperformed all other benchmarks in different local tasks although the advantage is narrower for the Brazil task.

For different tasks, the data might show leaning towards step-wise information or channel-wise information, especially for challenges in another domain. The assumption is that for a crop classification problem, temporal information should be crucial differentiator. Our preliminary results on the Brazil task provided validation to this assumption when we obtained a better performance (F1 score 0.94) with step-wise only model than channel-wise model (F1 score 0.70). Therefore, by incorporating this mechanism in a global data set, TGCNN yields better classification results than the other benchmarks overall. However, the imbalance issue in the data set still poses a challenge to the solution when it comes to multiple regional data subsets.

| Tasks | Model          | F1-score |
|-------|----------------|----------|
| Brazil| Random         | 0.9209   |
|       | MAML           | 0.9477   |
|       | Gated transformer | 0.962   |
|       | TGCNN (ours)   | **0.9739** |
| Kenya | Random         | 0.7812   |
|       | MAML           | 0.8315   |
|       | Gated transformer | 0.8056   |
|       | TGCNN (ours)   | **0.8543** |
| Togo  | Random         | 0.6736   |
|       | MAML           | 0.6509   |
|       | Gated transformer | 0.7644   |
|       | TGCNN (ours)   | **0.7948** |

Table 2. Model performance comparisons on different tasks
The modeling results are heavily impacted by regions that have significantly more samples.

4. Concluding Remarks

In this paper, we presented a state-of-the-art framework, Time Gated Convolutional Neural Network (TGCNN). The model takes advantage of temporal information and gating mechanisms for the crop classification problem. More than 90,000 geographically diverse samples formed a challenging task that requires analysis on multimodal data. TGCNN can allow modeling both spatial and temporal correlations effectively utilized convolutional neural network and gating mechanism. The results also paved the way for more in-depth study of machine learning techniques on earth observation time series data in future research and applications.

References

[1] Katherine Anderson, Barbara Ryan, William Sonntag, Argyro Kavvada, and Lawrence Friedl. Earth observation in service of the 2030 agenda for sustainable development. Geo-spatial Information Science, 20(2):77–96, 2017.
[2] Jing M Chen. Evaluation of vegetation indices and a modified simple ratio for boreal applications. Canadian Journal of Remote Sensing, 22(3):229–242, 1996.
[3] Emilio Chuvieco, Jonathan Li, and Xiaojun Yang, Advances in earth observation of global change, chapter The Role of Small Satellite Missions in Global Change Studies, page 1–15. Springer, 2010.
[4] Kevin Fauvel, Tao Lin, Véronique Masson, Élisa Fromont, and Alexandre Termier. Xcm: An explainable convolutional neural network for multivariate time series classification. Mathematics, 9(23):3137, 2021.
[5] Chelsea Finn, Pieter Abbeel, and Sergey Levine. Model-agnostic meta-learning for fast adaptation of deep networks. In Doina Precup and Yee Whye Teh, editors, Proceedings of the 34th International Conference on Machine Learning, volume 70 of Proceedings of Machine Learning Research, pages 1126–1135. PMLR, 06–11 Aug 2017.
[6] Bo-Cai Gao. Ndwi—a normalized difference water index for remote sensing of vegetation liquid water from space. Remote sensing of environment, 58(3):257–266, 1996.
[7] Anatoly A Gitelson, Yuri Gritz, and Mark N Merzlyak. Relationships between leaf chlorophyll content and spectral reflectance and algorithms for non-destructive chlorophyll assessment in higher plant leaves. Journal of plant physiology, 160(3):271–282, 2003.
[8] Patrick Kidger, James Morrill, James Foster, and Terry Lyons. Neural controlled differential equations for irregular time series. advances in neural information processing systems. Advances in Neural Information Processing Systems, 33:6696–6707, 2020.
[9] Hanxiao Liu, Zihang Dai, David So, and Quoc V Le. Pay attention to mlps. Advances in Neural Information Processing Systems, 34:9204–9215, 2021.
[10] Minghao Liu, Shengqi Ren, Siyuan Ma, Jiahui Jiao, Yizhou Chen, Zhiguang Wang, and Wei Song. Gated transformer networks for multivariate time series classification. arXiv preprint arXiv:2103.14438, 2021.
[11] Ignacio Oguiza. tsai-a state-of-the-art deep learning library for time series and sequential data. Retrieved April, 20:2021, 2020.
[12] John W Rouse Jr, R Hect Haas, JA Schell, and DW Deering. Monitoring the vernal advancement and retrogradation (green wave effect) of natural vegetation. Technical report, 1973.
[13] Sudhir Kumar Singh, Prosper Basommi Laari, Sk. Mustak, Prashant K. Srivastava, and Szilárd Szabó. Modelling of land use land cover change using earth observation data-sets of tons river basin, madhya pradesh, india. Geocarto International, 33(11):1202–1222, 2017.
[14] Corey N Thompson, Wexuan Guo, Bablu Sharma, and Glen L Ritchie. Using normalized difference red edge index to assess maturity in cotton. Crop Science, 59(5):2167–2177, 2019.
[15] Gabriel Tseng, Hannah Kern, Catherine Nakalembe, and Inbal Becker-Reshel. Learning to predict crop type from heterogeneous sparse labels using meta-learning. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 1111–1120, 2021.
[16] Gabriel Tseng, Ivan Zvonkov, Catherine Lilian Nakalembe, and Hannah Kern. Cropharvest: a global dataset for crop-type classification. In Thirty-fifth Conference on Neural Information Processing Systems Datasets and Benchmarks Track (Round 2), 2021.
[17] Jinru Xue and Baofeng Su. Significant remote sensing vegetation indices: A review of developments and applications. *Journal of sensors*, 2017, 2017.

[18] Zhiwei Yi, Li Jia, and Qting Chen. Crop classification using multi-temporal sentinel-2 data in the shiyang river basin of china. *Remote Sensing*, 12(24):4052, 2020.