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Phenology monitoring from multitemporal and multispectral satellite data: applications for crop monitoring and bloom detection

Monitoring seasonal changes in vegetation life cycle is called phenology and includes the study of crop growth and performance during developmental stages, which is an important aspect of agricultural management, enabling farmers to implement timely interventions that ensure optimal yields at the end of the season. Similarly, detecting the bloom period is very important for efficient beekeeping. The knowledge of the beekeeping flora of an area is necessary for the development of apiculture. Information such as the geographical distribution and the flowering period of various species are important for the planning of beehive transports by beekeepers and the reduction of production costs.
In the last two decades, the use of remote sensing in phenology has been the subject of significant research interest. Traditional phenology monitoring techniques required repeated observations of physical processes (e.g., flowering, bud development, leaf growth/senescence) by specialized personnel, thus were usually costly and time-consuming. The launch of non-commercial medium resolution satellites such as Sentinel 2, had led to the collection of a large quantity of earth observations (i.e. multispectral and multitemporal data), which can be used for tasks like crop classification [1] or land cover classification [2]. Recently, automated phenology stage/bloom detection approaches have been proposed based on either traditional machine learning (e.g. Random Forest [3], LightGBM, SVM) as well as deep learning networks for categorization or regression, (e.g. CNN, RNN, LTSM, U-Net) [4,5].

In the framework of the ongoing project SmartBeeKeep, funded by the EDK programme, we evaluated such architectures suitable for multitemporal multispectral data, based on Random Forest algorithm, Long Short-Term Memory (LSTM) networks [6] and Transformer-based self-attentional networks [7].
Two experiments were conducted: the former used a rice puddy production stage dataset, consisting of puddy rice observations from the region of west Java, Indonesia [5], while the latter studied the blooming stages of a beekeeping plant, namely "Cistus". Specifically, by combining in-situ observations as well as periodic measurements of the amount of balls found in pollen traps, an estimation of blooming state was achieved. These measurements were used as ground truth for estimating a model able to identify the blooming stage from multispectral images of the Sentinel-2 satellite. Furthermore, modern research has proven the great importance of the selective use of input data from neural networks that can lead to greater "explainability" of the produced results, which is desired for trustworthy machine learning /artificial intelligence (explainable AI) [7]. Therefore, a procedure to identify the relative importance of each multispectral band in this estimation process was also used.

References

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