Crop-Type Classification and Vegetation Monitoring Using Supervised Learning Model with Sentinel2 Satellite Time Series Data

Vaibhav Barsaiyan[1][0009−0000−0808−2408], Sravan S Sankar[2][0009−0001−7825−9819], and Shubham Thawait[3][0009−0006−5840−2995]

[1] Indian Institute of Technology Ropar, Ropar, India [2023csm1019@iitrpr.ac.in]
[2] Indian Institute of Technology Ropar, Ropar, India [2023csm1016@iitrpr.ac.in]
[3] Indian Institute of Technology Ropar, Ropar, India [2023csm1015@iitrpr.ac.in]

Abstract. A pixel-based large-scale temporal satellite imagery dataset named TimeSen2Crop[1] is used for the supervised classification of crop type classification. The publicly available dataset contains time series data related to 16 crop types in the country Austria. Deep learning models[6] like Temp CNN[3], Transformer[5], and Weighted LSTM models have been used to compare the dataset's quality performance in terms of accuracy. For every labeled pixel shadow, cloud, and snow pixels masks are applied for mitigation. Domain adaptation challenges[4] like Crop rotation (inconsistent land-cover maps for multiple years) in a specific area, and irregular distribution of crops are some of the major problems that need to be considered while training models.Stages of crop growth is also been analysed through NDVI(Normalized Difference Vegetation Index) spectral index,which tells current condition of crop and is observed every month for almost one year from September 2017 to August 2018.

Keywords: multispectral images, TimeSen2Crop, deep learning, Sentinel-2 dataset,Temp CNN[3],Transformer[5],Weighted LSTM,NDVI

1 Introduction

In today's world, crop type mapping and agricultural monitoring are very important for food security, efficient resource allocation, and sustainable land management. Advanced technologies of remote sensing and the availability of high-resolution satellite images like Sentinel 2 are used for agricultural applications.

The development of large benchmark datasets such as TimeSen2Crop[1] addresses the growing need for customized data to train and test advanced methods, especially those based on deep learning models. These datasets provide researchers and practitioners access to labeled samples of diverse temporal variations, crop types, and environmental conditions by enabling the robust algorithm of crop type mapping.

This article is devoted to the discussion of the role which the TimeSeN2Crop dataset can play in crop variety classification through the employment of several model methods. Specifically, we employ three distinct types of models: a Time-based Convolution Model utilizing Temporal Convolutional Neural Networks (TempCNNs), an Attention-based Model proposed by transformer architecture and a Recurrence-based Model that uses Weighted Long Short-Term Memory (LSTM) networks.

TimeSen2Crop is a massive dataset for agriculture with the label of about 1 million data points over 16 crops. Scale and diversity of the data sets are major factors in building deep models that are effective and can generalize on the diversity of landscapes. Besides that, its high temporal resolution that covers an entire agronomic year is essential for tracking crop cycles and trends. Through quality control audits and domain adaptation complications exploration, TimeSen2Crop helps to generate innovation in the agricultural monitoring industry and develop scalable solutions that will be useful in precision agriculture and environmental sustainability.

Vegetation monitoring using NDVI from satellite or aerial images quantifies the level of plant health by comparing deductions of near-infrared and red light reflection. This allows us to see the greenness and density of the vegetation and therefore we can monitor the changes in the cover, growth and vigor. NDVI is useful in locating the cause like that of drought or disease and therefore to control the failure of crop yield, biodiversity and ecosystems.

2 Dataset Description

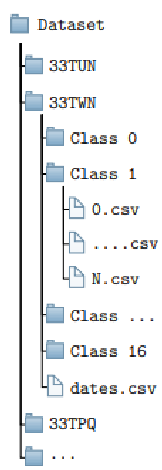

Fig. 1. File structure of the dataset[1]

TimeSen2Crop[1] is a pivotal dataset crafted within the framework of the ExtremeEarth project, generously funded by the European Union's Horizon 2020 research and innovation program (grant agreement No 825258). It stands as a cornerstone resource for advancing agricultural monitoring and remote sensing through its provision of more than 1 million meticulously labeled samples of Sentinel 2 time series imagery, capturing 16 distinct crop types. This dataset encapsulates an entire agronomic year, spanning from September 2017 to August 2018, and is imbued with meticulously corrected atmospheric samples, coupled with comprehensive annotations regarding snow, clouds, and shadows.

The TimeSen2Crop[1] layout is organized around Sentinel 2 tiles, which are organized into 16 folders, each corresponding to a specific crop. These folders contain a wide range of data including collection dates stored in CSV files, arranged chronologically from the first collection to the last data. In each crop characteristic folder individual labeled samples are housed in CSV files, providing detailed multispectral[2] temporal signatures. This dataset consists of a matrix in which each row indicates the date of acquisition, while each column indicates a spectral band, with blue (B2), green (B3), red (B4), and four vegetation red edges (with B5, B6, B7, and B8A). and two shortwave-infrared (SWIR) bands (B11 and B12). In addition, the final column of the CSV files describes important information about the pixel conditions, classifying them as clear (0), cloudy (1), shadow (2), or snowy (3).

This carefully constructed dataset not only serves as a resource for improving crop variety classification but also provides fertile ground for pioneering research efforts in agricultural monitoring and remote sensing Researchers and innovators can use TimeSen2Crop[1] to explain the complex dynamics of agricultural landscapes, promote sustainable practices, and achieve informed decision making.

The seminal work of Weikman, Paris, and Brujon (2021) is a valuable resource for those who wish to deepen their understanding of dataset origins, methods, and performance analysis This review issue of the IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing examines the challenges[4] of TimeSen2Crop[1], Remote sensing enhances scholarly discourse in agriculture by illuminating its architecture, operational considerations, and applicability.

3 Methods

The following types of models were used to do the task:

- **Time-based Convolution Model**
- **Attention-based Model**
- **Recurrence-based Model**

TimeSen2Crop stands out for several reasons:

1. **Time-based Convolution Model:** In the time-based convolution model, the Temp CNN[3] model is used. Temporal Convolutional[9] Neural Networks (TempCNNs) are a type of convolutional[9] neural network used for processing time-series data. It captures complicated temporal patterns irrespective

of the locations in the input sequence while at the same time maintaining translation invariance.

2. **Attention-based Model:** In the Attention-based Model we use the transformer[5] model, which captures the sequence of input data in parallel and also from distant parts of the sequence it takes context information which will be useful to improve performance by taking into account the long-range dependency.
3. **Attention-based Model:** In the Recuurence-based Model, the weighted LSTM[7] model is used where advantage of using this is that it eliminates the vanishing and exploding gradient problems encountered in traditional RNNs, LSTM[7] also captures long-term dependencies since it has memory cells to store and propagate across.

4 Divisions of Tiles and Selection of tiles for Training,Testing and Validation

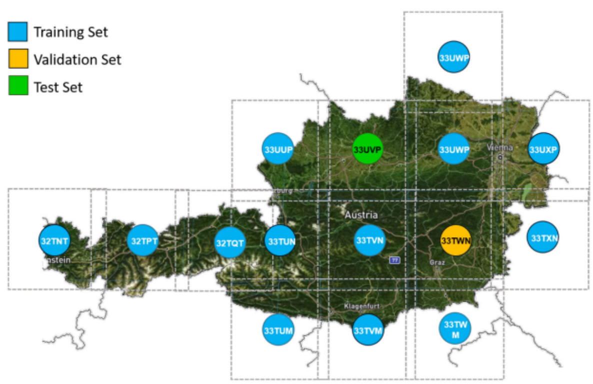

Fig. 2. Spatial division of the Sentinel 2 tiles into training, test and validation is reported in blue, yellow, and green, respectively.[1]

Austria is divided into 15 Sentinel 2 tiles, shown in Fig.2 .From these tiles, Samples were extracted to form three distinct sets: training (13 tiles), testing (1 tile), and validation (1 tile). Each set contains labeled pixels, with the training set having 822,843 (76.71%), the test set 133,419 (12.43%), and the validation set 116,369 (10.84%). Notably, this setup ensures the test area spans 12,056.4 km$^{\mathbf{2}}$ and remains statistically independent from the training areas due to the absence of spatial overlap between training and test samples. Fig.1 illustrates the delineation of training, testing, and validation sets within the Sentinel 2 tiles.

5 Result and Analysis

5.1 Training and Accuracy curves for Models

1. **Recurrence-based Model - Weighted LSTM**

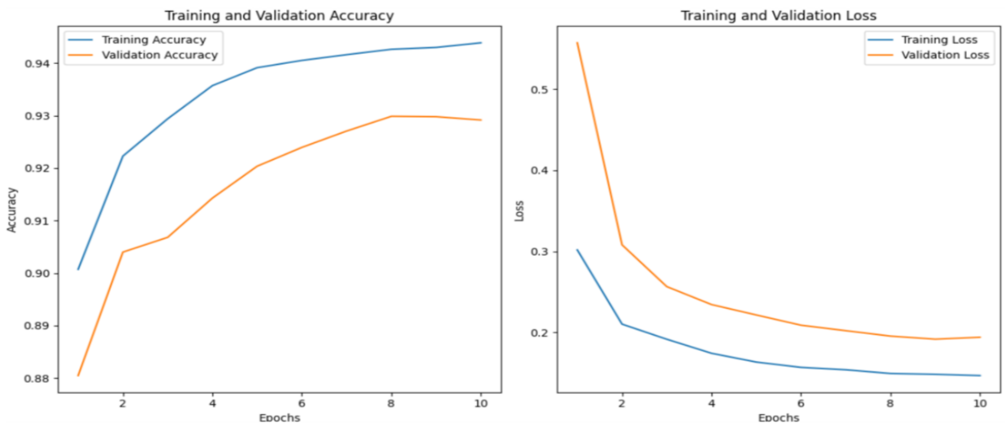

Fig. 3. Graph of Validation accuracy and Validation Loss for crop Legume

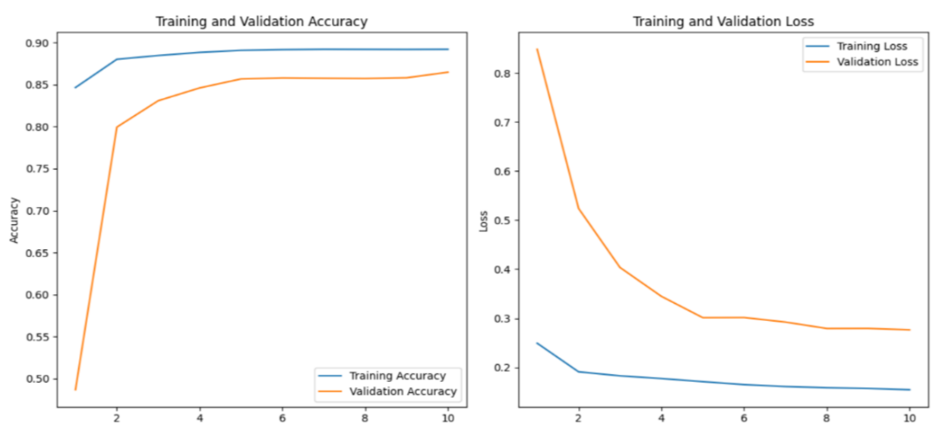

Fig. 4. Graph of Validation accuracy and Validation Loss for crop Sunflower

2. **Attention-based Model: Transformer Model**
3. **Time-based Convolution Mode-TempCNN**

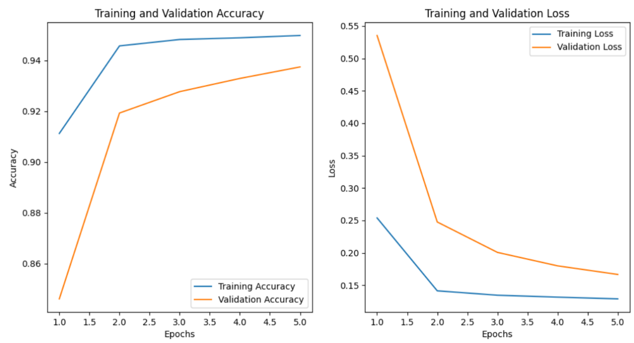

Fig. 5. Graph of Validation accuracy and Validation Loss for crop Winter Triticale

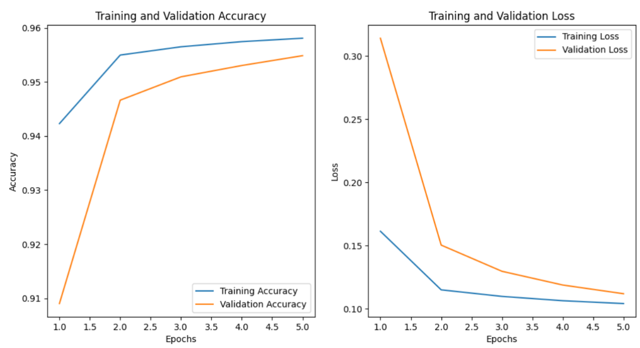

Fig. 6. Graph of Validation accuracy and Validation Loss for crop Winter Wheat

Fig. 7. Graph of Validation accuracy and Validation Loss for crop Sunflower

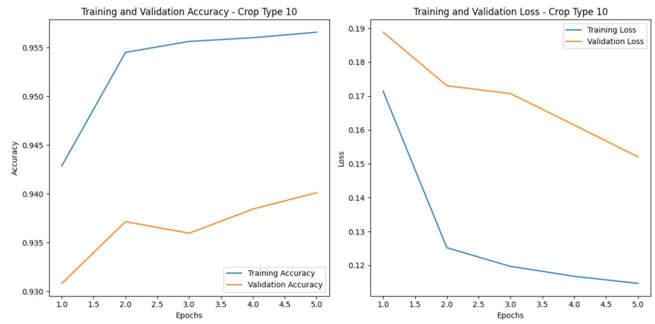

Fig. 8. Graph of Validation accuracy and Validation Loss for crop Beet

5.2 Analysis

Crop Type	Transformer			Temp CNN			Weighted LSTM		
	F1 SCORE(%)	LOSS(%)	ACCURACY(%)	F1 SCORE(%)	LOSS(%)	ACCURACY(%)	F1 SCORE(%)	LOSS(%)	ACCURACY(%)
Legumes	94.27	17.51	93.75	95.87	12.07	95.36	94.94	13.88	94.6
Grassland	91.84	21.02	92.13	92.98	18.97	92.79	93.03	18.52	92.87
Maize	95.96	11.83	95.68	96.54	9.31	96.4	93.98	11.83	95.88
Potato	92.98	19.26	93.07	95.31	13.21	94.97	92.98	19.26	93.07
Sunflower	90.92	38.25	89.82	91.73	27.85	92.58	90.82	38.25	89.82
Soy	96.02	11.72	95.77	96.83	8.47	96.71	96.49	9.6	96.34
Winter Barley	95.68	11.36	95.71	96.48	9.18	96.33	96.34	9.78	96.12
Winter Caraway	92.26	26.95	91.95	93.02	18.81	93.26	92.47	20.96	92.81
Rye	92.66	19.25	92.98	94.46	15.13	94.21	94.25	16.35	93.85
Rapeseed	95.79	14.04	94.97	96.52	9.98	96.27	96.15	10.90	95.87
Beet	96.14	12.21	95.90	97.05	8.32	97.06	96.48	9.62	96.44
Sprint Cereals	92.99	18.92	93.13	94.44	15.02	94.24	94.34	15.88	94.09
Winter Wheat	95.97	10.81	95.89	96.7	8.32	96.7	96.61	9.13	96.33
Winter Triticale	93.72	16.79	93.77	94.79	13.61	94.74	94.71	14.44	94.49
Permanent Plantation	95.00	17.63	94.96	95.41	12.52	95.86	95.38	13.22	95.85
Other Crops	93.21	18.57	93.39	94.61	14.96	94.3	94.06	15.91	94.07

Fig. 9. Contains the F1 score ,Accuracy and Loss by each model for every crop

On the basis of above table we have F1 score , loss percentage and accuracy percentage for each model, so by using this values we can analysis.

(a) **Transformer:**
F1 Score: Here the Transformer model has achieved F1 scores ranging from around 91.84% to 96.14% across different crop types.
Loss Percentage : Loss percentages is varying between approximately 10.81% to 38.25% which indicating a range of performance in terms of model fit.
Accuracy Percentage: Accuracy percentages range from approximately

89.82% to 97.06% and this is demonstrating the model's ability to correctly classify crop types.

(b) **Temp CNN:**
F1 Score : F1 scores for the Temp CNN model range from around 91.73% to 96.83% across different crop types.
Loss Percentage : Loss percentages vary between approximately 8.32% to 27.85%,that is suggesting relatively better model fit as compared to the Transformer model.
Accuracy Percentage : Accuracy percentages range from approx 89.82% to 97.06% , indicating the comparable performance to the Transformer model in terms of classification accuracy.

(c) **Weighted LSTM:**
F1 Score: The Weighted LSTM model achieves F1 scores ranging from approximately 92.98% to 96.61% across different crop types.
Loss Percentage: Loss percentages vary between approximately 9.13% to 20.96%, indicating relatively better model fit compared to both the Transformer and Temp CNN models.
Accuracy Percentage:Accuracy percentages range from approximately 92.81% to 96.44% which is demonstrating competitive performance in correctly classifying crop types.

6 Vegetation Monitoring

Vegetation monitoring stands true to this definition — continuous viewing and assessment of plant growth and wellness, using methods such as remote sensing and survey monitoring. Through the analysis of changes in vegetation patterns over time, it can be a useful tool in knowing the ecosystem health, land use patterns and environmental shifts, which can be applied to conservation and sustainable land management.
Method we used for vegetation monitoring is:

- **NDVI (Normalized Difference Vegetation Index)**

NDVI (Normalized Difference Vegetation Index) is now one of the most used methods of vegetation monitoring in remote sensing and agricultural research. NDVI is thus a product of the satellite imagery analyses that calculate vegetation health and density in a certain area of interest. It follows the fact that green vegetation usually absorbs the majority of the visible light that falls on it and reflects enormous amount of the near infrared energy. NDVI is a measure of the density and state of vegetation which is obtained by the comparison of the reflected near-infrared and visible light.

6.1 Results

From figure 12 and figure 13,taking 2 crops we can see how for each month from Sep 2017 to Aug 2018,the crop condition varies.Depending on NDVI

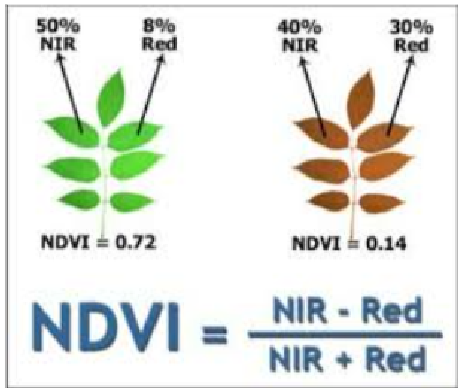

Fig. 10. Formula for calulating NVDI

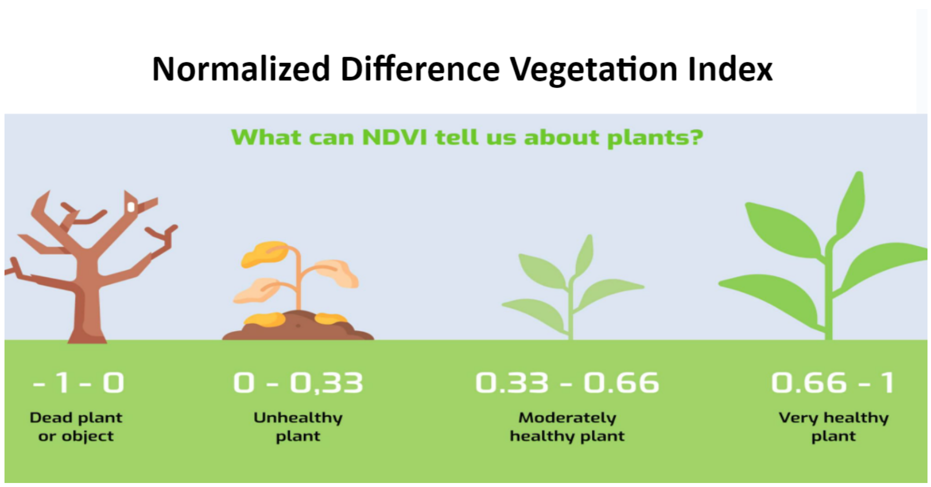

Fig. 11. Vegetation monitoring of crop on the basis of NVDI value

value cross some threshold,it can be categorised into four different categories as shown in fig 11

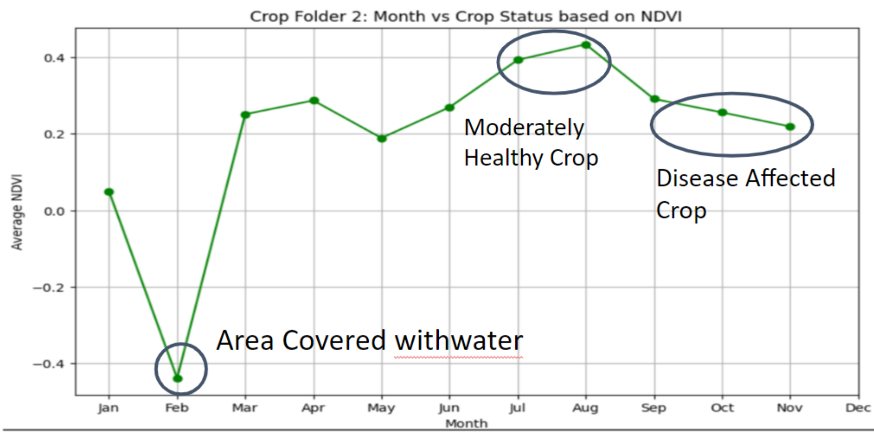

Fig. 12. Sample Output of Crop NDVI Variation for Crop2

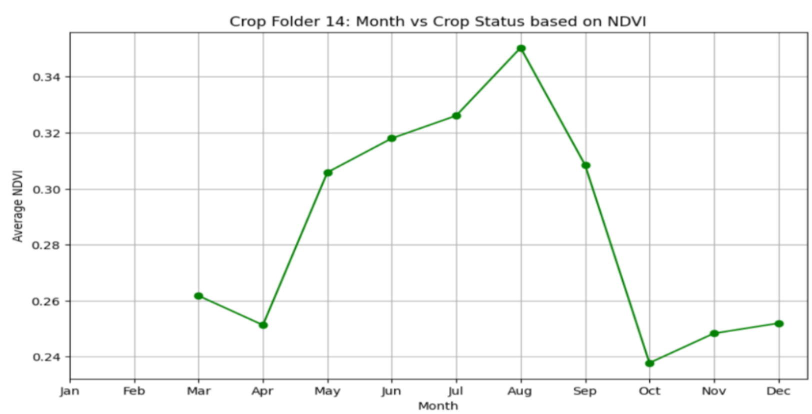

Fig. 13. Sample Output of Crop NDVI Variation for Crop14

7 Challenges

When working with a dataset and applying a models, especially with multiple CSV files, several challenges[4] might arise regarding the interpretation and utilization of the results. Here are some potential challenges:

(a) **Data Quality and Consistency:**Provide that the accuracy and dependability of samples with labels in benchmark datasets are respected.
(b) **Temporal and Spatial Variability:** Address challenges in capturing and interpreting dynamic changes in vegetation cover, growth, and health across different regions and time periods.
(c) **Overfitting:**Overfitting happens when the model memorizes training data instead of capturing underlying patterns.
(d) **Model Interpretability and Transparency:** Here interpretability and transparency of vegetation monitoring models for user understanding so that user can trust.
(e) **Performance Monitoring and Maintenance:**This hard to monitor Continuously model performance also update them with new data or changes in data distribution.

8 Future Scope

In the agriculture field, leveraging datasets containing images captured at different times offers numerous opportunities for improving crop[8] monitoring, yield prediction, pest detection , and overall farm management.

(a) **Crop Monitoring and Management:** The continual crop tracking through the images helps to observe the plant health , development and growth.
(b) **Yield Prediction and Forecasting:**Allied past crops yielding images together and environmental data enables precise prediction of future yields.
(c) **Precision Agriculture and Variable Rate Application:** The quantification of crop fitness variability provides a basis for optimal resource allocation which in turn , saves cost and the environment.

9 Conclusion

In conclusion our study has clearly shown the efficiency of the three supervised models accurately in classifying the crops types .The comparison of training and validation accuracy as well as loss curves are providing the insights into the performance and generalisation capabilities of these models .Also our approach has successfully accomplished the boundary classification through map type mapping for specific area . By utilizing the spectral index, we have analyzed the growth stages of all crops nearly a year, we are determining the plant health and identifying the optimal location for crop growth and harvesting times . Overall , these all findings underscore the potential of our methodology for enhancing crop monitoring , crop management and decision making in agricultural practices.

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