A neural network approach for real-time monitoring of cannabis sativa L. germination

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Abstract

One of the primary challenges in detecting crop germination in seedbeds using computer vision is the difficulty of accurately analysing cases of overlapping seedlings. This study investigates the effectiveness of Convolutional Neural Network (CNN) models and Long Short-Term Memory (LSTM) models in addressing this issue. Utilizing a substantial dataset comprising over 80,000 labelled images of Cannabis Sativa plants, our research aims to compare the performance of standalone CNN models with hybrid architectures (CSS+LSTM model). A noteworthy aspect of our experimental methodology is the deliberate omission of data augmentation techniques during dataset preparation. This decision enables us to evaluate the inherent quality and utility of our curated dataset without introducing artificial modifications. Furthermore, recognizing the significance of incorporating a temporal component in germination detection, we conduct a specific assessment of the hybrid model (CNN+LSTM) against the standalone CNN model. Through comprehensive experimentation and analysis, we evaluate the relative effectiveness of each model in accurately classifying germination status across different levels of seedling overlap. Preliminary results reflect a better performance of the hybrid model compared to the standalone CNN model. However, it is crucial to consider the computational resources, time, and effort required for training and testing the model. Thus, our study provides valuable insights into the intricate interplay among model architecture, dataset characteristics, and the complexity of the germination detection task. Moreover, this research contributes to the advancement of practical applications of deep learning methodologies in agricultural monitoring, emphasizing the necessity of tailored model designs to overcome the unique challenges encountered in greenhouse environments.

Keywords: CNN, LSTM, Computer vision, Germination detection, *Cannabis sativa*.

1. Introduction

In contemporary agriculture, a thorough monitoring of germination processes holds critical significance, representing a crucial stage in crop cultivation that directly impacts subsequent growth and yield outcomes. Among the myriad challenges faced by farmers, the accurate detection of germination, particularly amidst the complexities of overlapping seedlings, emerges as an obstacle. The proliferation of dense vegetation within seedbeds presents a challenging scenario, where traditional manual inspection methods prove laborious, time-consuming, and prone to inaccuracies. Consequently, the adoption of advanced technological solutions becomes imperative to streamline this essential agricultural task.

Real-time monitoring of germination processes heralds a paradigm shift in agricultural practices, offering unparalleled insights into crop development dynamics and enabling proactive interventions to optimize cultivation outcomes. The arrival of neural network approaches, particularly Convolutional Neural Networks (CNNs), Long Short-term Memory Networks (LSTMs), and their hybrid architectures, has revolutionized image analysis tasks, empowering researchers, and practitioners with sophisticated tools for pattern recognition and decision-making.

CNNs excel at extracting complex spatial features from visual data, making them well-suited for tasks such as object detection and classification. LSTMs, on the other hand, are adept at modelling sequential data and capturing temporal dependencies, thus proving invaluable in analysing time-series information. The fusion of these two architectures in hybrid models combines the strengths of both approaches, offering enhanced capabilities for analysing complex spatio-temporal patterns in image datasets.

Against this backdrop, our research endeavours to address the pressing need for effective germination detection in seedbeds, with a specific focus on supporting farmers in their cultivation practices. Our goal is to analyse if a hybrid model of CNN and LSTM neural networks is able to detect effective germination, including scenarios with overlapping seedlings, against single models like CNN neural networks. By harnessing the power of neural network methodologies, we aim to develop a robust framework capable of accurately identifying germination events amidst the challenges posed by overlapping seedlings. Through experimentation and analysis, our objectives encompass not only the refinement of model architectures but also the validation of real-time monitoring capabilities to empower farmers with timely insights into crop development stages.

Furthermore, our contribution addresses cannabis sativa cultivation concerns, where overlapping seedlings pose unique challenges due to the strict regulations on the number of plants allowed for cultivation. In this context, enabling real-time germination monitoring is essential for farmers. Thus, by focusing on cannabis sativa, we aim to provide tailored insights and solutions that meet the unique needs of cannabis growers, thereby advancing the practical applications of deep learning methodologies in agricultural monitoring.

In the next section, we review several studies that focus on automatic germination detection using artificial intelligence techniques.

2. Background

In this section, we present an overview of the existing literature on the automatic detection of plant germination employing Artificial Intelligence (AI) techniques. To ensure a thorough and wide-ranging analysis, we conducted a literature review across three digital libraries: Scopus, IEEE Xplore, and Springer. Our objective was to identify and analyse studies that have employed AI for automatic germination detection. We performed a general query *("detection" AND "germination" AND "agriculture"*) on the databases' search tools to find relevant studies. We then filtered the results to include only those studies that specifically addressed automatic germination detection using AI techniques. The following analysis provides a concise summary of the principal findings and methodologies from the reviewed studies.

Most of the found studies in literature are related to seed germination detecting the radicle in early stages of germination. Kim et al. (2010) introduced a detailed process for extracting seed characteristics crucial for germination detection through image processing techniques. The proposed methodology involves circle detection, noise filtering, image segmentation, thresholding, morphological operations, and object labelling, all tailored to optimize system performance. The proposed procedure automates seed analysis by detecting Petri dishes, segregating background from seeds, and computing essential seed parameters for subsequent analysis.

Nguyen et al. (2018) presented a system for automating the evaluation of rice seed germination rates using computer vision and machine learning. The proposed method employed U-Net model for seed segmentation, followed by distance transform and thresholding for seed detection, and ResNet model for seed classification. Results demonstrated the superiority of Convolutional Neural Networks over traditional methods, with F1-scores of 93.38% and 95.66% for segmentation and classification tasks, respectively.

Shadrin at al. (2019) integrated AI into a low-power sensing system for seed germination detection. By implementing a custom CNN model, researchers achieved significant accuracy, with an average Intersection over Union (IoU) score of 83% on the test dataset and 97% seed recognition accuracy on the validation dataset. The researchers demonstrated the potential benefit of seed germination automatic detection at industrial facilities thought Internet of Things (IoT) applications.

Chaivivatrakul (2020) explored automated methods for determining seed germination rates using the top of paper germination method. This study encompassed four-time repetitions of chili and guinea seeds germination with two sets of germination groups, totalling 400 seeds each. Besides, two detection methods were proposed and compared: binary thresholding and maximum likelihood based on color analysis. Results indicated both methods achieved accuracy rates exceeding 93%, with binary thresholding being lightweight and suitable for resource-limited environments, while maximum likelihood demonstrated flexibility to varying light conditions.

In addition, Grant et al. (2023) developed an AI system using CNNs and image processing techniques to detect corn seed germination. This study used a dataset of 400 images of corn seeds at various germination stages and used the CIELAB color model for radicle and seed segmentation detection. The employed AI technique was k-fold cross-validation, and the model achieved a detection accuracy of 98.14%.

Regarding the use of mobiles, Ahmad et al. (2023) employed smartphone cameras in combination to image processing to detect fungal infections in chickpea seeds. In this study, images of 15 seeds were collected every 24 hours for three days. Two spectral indexes combining different colour bands were used for detection. Combining both indexes achieved an average accuracy of 96.66% and precision of 93.33%, significantly outperforming individual indexes. In this case, the selected artificial intelligence technique was Discriminant Analysis. This method shows promise for early fungal infection detection and could be implemented as a mobile application for practical use.

In another study, Donapati et al. (2023) introduced a novel fusion model for seed detection and germination analysis in precision agriculture. By combining U-Net for seed segmentation and CNN for classification, the model achieves effective seed germination analysis. The model was implemented on the NVIDIA Jetson Nano embedded GPU platform. Results showed notable performance metrics, including 0.91 pixel accuracy, 0.84 intersection over union (IoU), and 0.90 precision, outperforming ResNet50, Inception, and LeNet. The implemented model also exhibited low latency of 0.26 ms, demonstrating its suitability for real-time applications in precision agriculture.

In a more recent study, Chen et al. (2024) presented a novel techniques and methodology for seed vigor detection in maize cultivation. Advanced algorithms like HSI and 3DCNN were utilized, alongside RGB imaging, to develop robust models for classifying corn seed vitality. Also, researchers presented a new dataset comprising pictures of corn seeds taken under six contrasting conditions. This dataset enabled accurate prediction and grading of seed germination and vigor, enhancing the validity of non-destructive seed vigor identification in smart agriculture.

Regarding the detection of leaves and plants, Ma et al. (2022) presented a rapid and accurate method for detecting peanut seed germination in large fields. The researchers combined deep learning-based object detection (OD) with unmanned aerial systems (UAS) to identify early germination. For the analysis, Faster RCNN and SSD object detection models were used to compare multispectral imagery from a MicaSense Rededge camera. The results showed Faster RCNN achieved higher accuracy, although with longer computation times. Notably, RGB-based detection performed comparably to multispectral imagery, indicating cost-effective alternatives. Resnet-34 was identified as the optimal backbone for Faster RCNN.

As evidenced by numerous studies found in the literature, artificial intelligence techniques have been increasingly utilized to automate the detection of germination. However, most of these studies have primarily concentrated on radicle detection and have been conducted within laboratory settings. While only one study has ventured into field-based detection, it relied on costly UAV systems for image capture. In contrast, our study focuses on the detection of germinated plants, specifically targeting the identification of cotyledon and leaves within the seedbed. This approach aims to alleviate the burden on farmers by reducing manual effort. Additionally, we conducted our study within a greenhouse environment, offering a more accessible and controlled growing environment for farmers.

Next, we outline the prerequisites and methodology employed in our proposal.

3. Materials and Methods

This section provides an overview of the image dataset employed in our study, the selected deep learning models considered in the analysis, and the entire methodology we followed to conduct the research. Frist, we present some details regarding the image dataset.

3.1. Image dataset of Cannabis Sativa L. plants germination

To conduct a comprehensive comparative analysis of neural network models for detecting *Cannabis sativa* germination in seedbeds, we curated an extensive dataset comprising over 80,000 images of seedbed cells. This dataset was meticulously assembled to capture various stages of germination, ensuring a robust input for training, and evaluating our models.

The dataset was created in a controlled experimental setup established within a greenhouse to simulate typical growing conditions of Cannabis Sativa L. plants. The setup included a high-resolution camera in a zenithally position over the seedbeds. The camera was connected to an embedded system (Raspberry Pi). This configuration enabled automated image capture, ensuring consistent imaging conditions throughout the experiment.

Germination experiments were conducted over various periods of 14 days each one. During each period, the camera system captured images every hour to document the progression of germination. Since each image consisted of an entire seedbed, it was necessary to cut them into individual cells for detailed analysis. This process yielded a dataset that encompassed images with a diverse range of germination stages, including instances of overlapping seedlings from neighbouring cells. Figure 1 depicts a sample image captured by the camera, along with examples of extracted cell images.

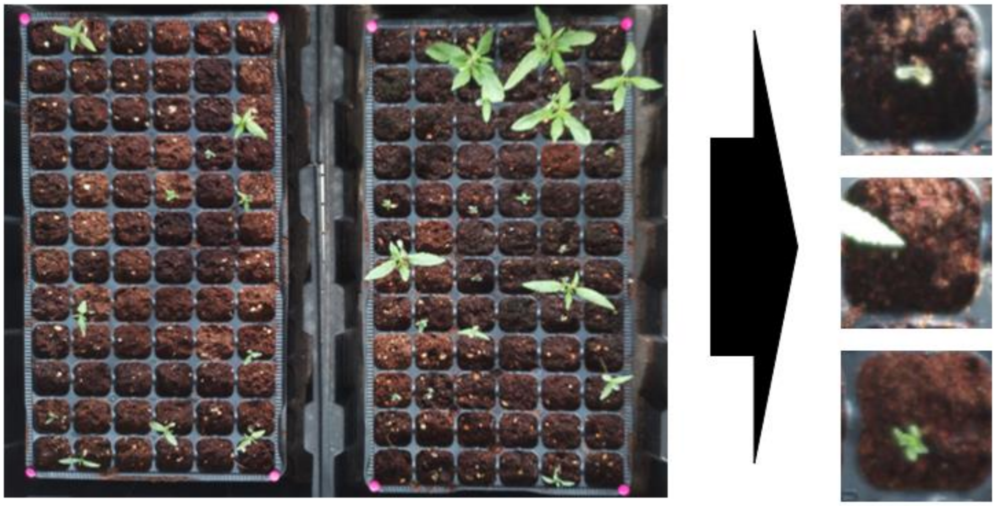

Figure 1. Seedbed image and samples of cells extracted from the seedbed image.

Each seedbed image was processed to extract individual cells, resulting in a collection of cell-level images. Then, the images were carefully labelled based on their content in the following categories:

- Germinated Plant: Cells containing a germinated Cannabis Sativa L. plant.
- Overlapping Plant: Cells where the plant is overlapped with seedlings from neighbouring cells.
- Non-germinated Cell: Cells without any visible germination.

This labelling process was critical to ensure the accuracy of our dataset and to facilitate the training and evaluation of the selected neural network models.

3.2. Models' architectures

We developed two distinct neural network models for the classification task:

- Convolutional Neural Network (CNN): The CNN architecture was designed to extract spatial features from the cell images. It consisted of multiple convolutional layers followed by pooling layers, culminating in fully connected layers for classification. Figure 2 shows the architecture of the CNN model. The primary focus of this model was to identify germination and overlapping plants based on spatial patterns within the images.

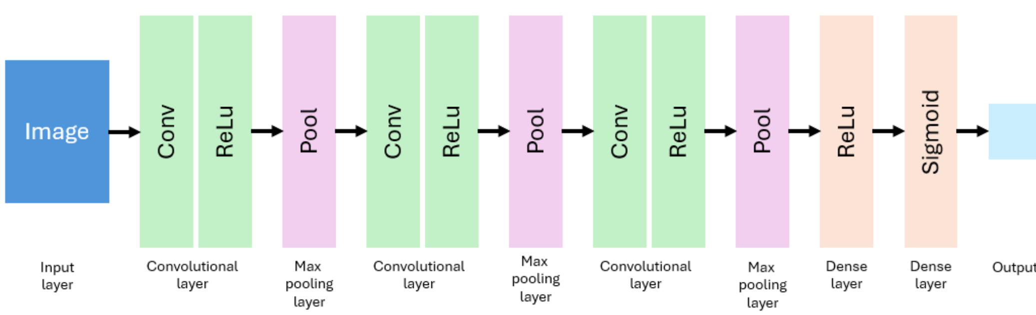

Figure 2. CNN model's architecture.

- Hybrid Model (CNN+LSTM): We created an hybrid model combining the spatial feature extraction capabilities of CNN with the temporal analysis capabilities of Long Short-Term Memory (LSTM) networks. The CNN component, identical to the standalone model, was responsible for extracting features from the images. These features were then fed into an LSTM layer, which captured temporal dependencies across the sequence of images. This architecture was designed to enhance the model's ability to detect germination events by considering the temporal progression of the germination process. Figure 3 shows the architecture of the CNN model.

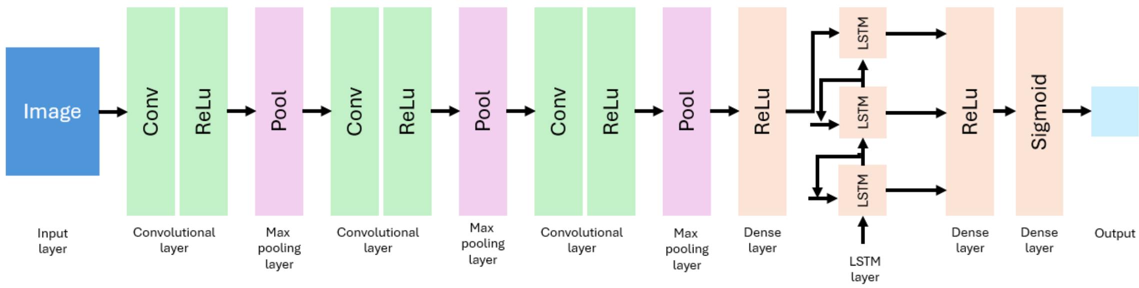

Figure 3. Hybrid model's architecture

Next, we outlined the experimental configuration employed to train, test, and validate the selected network models.

3.3. Experimental setup

Both models were trained using the created image dataset. The dataset was split into training, validation, and test sets to ensure a rigorous evaluation. The training process involved using standard backpropagation techniques with appropriate loss functions and optimisation algorithms. During training, key performance metrics such as accuracy, precision, recall, and F1 score were monitored to evaluate the models' effectiveness.

Upon completion of the training phase, the performance of the two models was compared based on their ability to accurately classify germination status in the seedbed images. The evaluation was conducted using the test set, and the results were analysed to assess:

- Accuracy: the overall correctness of the model's predictions. This metric is calculated based on the Equation 1.

$$\text{Accuracy} = \text{Number of correct predictions} / \text{Total number of predictions} \quad (1)$$

- Precision: it can be defined as the ratio of correctly predicted positive observations to the total predicted positives. The precision reflects models' ability to correctly identify germinated and overlapping plants. Precision is calculated based on Equation 2.

$$\text{Precision} = TP / (TP + FP) \quad (2)$$

Where TP is True Positive

FP is a False Positive

- Recall: also known as sensitivity or true positive rate. Recall measures the ability of a classification model to identify all relevant instances within a dataset. It is calculated based on Equation 3.

$$\text{Recall} = TP / (TP + FN) \quad (3)$$

Where TP is True Positive

FN is a False Negative

- F1 Score: is a metric used to evaluate the performance of a classification model, balancing both precision and recall. It is the harmonic mean of precision and recall, providing a single measure that captures both aspects of model performance. F1 score is calculated based on Equation 4.

$$\text{F1 Score} = 2 \times (\text{Precision} + \text{Recall}) / (\text{Precision} \times \text{Recall}) \quad (4)$$

Additionally, the computational resources, time, and effort required for training and testing each model were analysed to understand their practical feasibility for real-time monitoring applications.

The training and testing of the models was conducted on a high-performance workstation equipped with the following hardware specifications:

- Graphics Processing Unit (GPU): The training utilized CUDA for accelerated computation, specifically leveraging a Nvidia Quadro T2000 GPU with 4GB of dedicated GPU RAM. This setup facilitated efficient parallel processing and significant reductions in training time.
- Central Processing Unit (CPU): An Intel Xeon W-10855M processor, operating at 2.8 GHz with 6 cores, was used for general computation tasks. This processor ensured reliable performance and supported the GPU in tasks that required CPU intervention.
- System Memory: The system was equipped with 32 GB of RAM, providing ample memory for handling large datasets and ensuring smooth operation during the training process.

Besides, the training, testing and validation were conducted during 35 epochs with a batch size of 48.

Our research specifically focuses on the challenges posed by overlapping seedlings in *Cannabis sativa* L. cultivation. Regarding cultivation regulations for this crop, we aim to provide custom-made insights and solutions that cater to the unique needs of cannabis growers. The detailed analysis and comparative evaluation of CNN and hybrid models seek to contribute to the advancement of deep learning methodologies in agricultural monitoring, highlighting the importance of model design in overcoming the specific challenges encountered in greenhouse environments.

In the next section, we present the obtained results for this research.

4. Results

After conducting training, test and validation of the two analysed models, Figure 4 shows the performance comparison between the Convolutional Neural Network (CNN) model and the hybrid model over a span of 35 epochs. These charts highlight the improvements achieved by the hybrid model in terms of validation accuracy and validation loss.

Regarding the models' accuracy, section left of Figure 4 depicts the results for both the CNN and hybrid models across epochs. The blue line with circle markers indicates the validation accuracy of the CNN model, while the green line with circle markers represents the validation accuracy of the hybrid model. It can be seen from the chart that the hybrid model achieves higher accuracy at almost every epoch, demonstrating its better capability in correctly identifying the classes. Notably, the validation accuracy of the hybrid model remains above 0.97 throughout the training period, while the CNN model shows slightly lower performance, especially in the initial epochs.

By other hand, the right section of Figure 4 presents the validation loss for both the CNN and hybrid models over the same epochs. As mentioned, validation loss measures the discrepancy between the predicted and actual class labels, with lower values indicating better model performance. The red line with circle markers represents the validation loss of the CNN model, and the magenta line with circle markers represents the validation loss of the hybrid model.

The hybrid model achieved lower validation loss compared to the CNN model. This trend indicates that the hybrid model not only makes more accurate predictions but also has a better fit to the validation data. The reduction in validation loss is particularly significant in the early epochs, where the hybrid model quickly converges to lower loss values. This suggests that the hybrid model is more effective in learning from the training data and generalising to unseen samples.

In terms of overall performance, the Figure 4 shows that the hybrid model, which integrates both Convolutional Neural Networks (CNN) and Recurrent Neural Networks (LSTM), provides substantial improvements over the CNN model alone. The hybrid model achieves higher validation accuracy and lower validation loss, indicating better performance in classifying samples as germinated or non-germinated. These results underscore the enhanced capability of the hybrid model to leverage both spatial and temporal features, leading to more accurate and reliable classification outcomes.

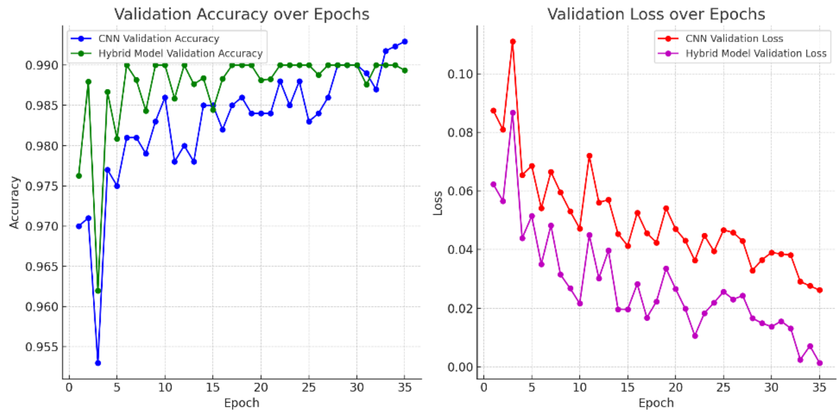

Figure 4. Accuracy and loss results for CNN and Hybrid model.

Regarding resource and time consumption, it is important to note that the hybrid model incurs higher costs to achieve its enhanced performance. Its complex architecture, especially the recurrent layers, requires extensive computations, resulting in significantly longer training times. Moreover, the hybrid model demands more computational resources. For example, the CNN model took 5 hours, 38 minutes, and 23 seconds to complete training, testing, and validation over 35 epochs. In contrast, the hybrid model required 9 hours, 22 minutes, and 45 seconds for the same process, highlighting the additional time and resource investment needed for the hybrid model.

Optimizing the hybrid model also requires more effort and expertise. Extensive hyperparameter tuning and a deeper understanding of both CNN and LSTM functionalities are essential for effective optimization. During validation and testing, the hybrid model consumes more time as each sample undergoes both convolutional and sequential processing, affecting overall evaluation efficiency. While the hybrid model achieves better classification performance, these improvements must be weighed against the higher costs in time, computational resources, and optimization effort. These trade-offs are important considerations for implementing hybrid models in practical applications.

5. Conclusions

The results of this study show a better performance of the hybrid model in classifying the samples into germinated (G) and non-germinated (NG) classes compared to the CNN model. The validation accuracy of the hybrid model exceeded that of the CNN model across all epochs. This finding indicates the hybrid model's enhanced ability to correctly identify germinated and non-germinated samples, reflecting its robustness and effectiveness in handling the classification task. Nevertheless, hybrid model consumes more time and effort than the CNN model to achieve that performance.

Furthermore, the validation loss for the hybrid model was significantly lower than that of the CNN model. Lower validation loss indicates that the hybrid model made fewer errors in its predictions, further confirming the usefulness of having series of images in the training dataset and memory capability in the model. The incorporation of temporal features such as the day and hour of image capture enabled the hybrid model to utilise additional context, leading to more informed and accurate predictions. This integration of temporal data proved to be a critical factor in enhancing the model's classification capacity. By leveraging both spatial and temporal features through the combination of convolutional neural networks (CNN) and recurrent neural networks (LSTM), the hybrid model was able to achieve superior classification results.

Overall, the hybrid model's ability to integrate CNNs with LSTM networks to leverage both spatial and temporal features represents a significant advancement. The superior classification results achieved by the hybrid model underscore its potential for practical applications in seed germination analysis and similar domains requiring precise classification of time-sequenced visual data. These findings pave the way for further exploration and optimization of hybrid models, promising even greater improvements in performance and applicability across various fields of machine learning and artificial intelligence.

For future work, we plan to compare the hybrid model with other alternative models and techniques to validate its utility in detecting effective germination of *Cannabis sativa* L. plants. This comparative analysis will help determine the robustness and generalizability of the hybrid model, ensuring its effectiveness and reliability in practical applications. Additionally, exploring various optimization strategies and model enhancements will be crucial in further improving its performance and efficiency.

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