Convolutional Neural Network Based Flood Detection Using Remote sensing images

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Abstract

The proposed system uses pre-existing CNN, namely Alex Net, for mapping flooding regions using remote sensing images and the application of high-level spatial features for classification of satellite imagery has been underrepresented. This study aims to address the lack of high-level features by proposing a classification framework based on convolutional neural network (CNN) to learn deep spatial features for flood mapping using optical remote sensing images. Designing a fully trained new convolutional network is impossible due to the limited amount of training data available in most remote sensing studies. Every patch is normalized and resized to feed the network. The designed convolution kernels are then applied to the input patch to generate some normalized features. Each feature highlights a group of similar objects. The kernels are designed to highlight the group of pixels that decrease the loss function. These high-level features mostly rely on the spatial information in the patches. In detection of wetland on flood affected regions using remote sensing images accuracy was employed. The classification results obtained by the deep CNN were compared with those supported based on well-known ensemble classifiers. In this classification scheme is the first attempt, investigating the potential of fine-tuning pre-existing CNN, for cowl mapping of flooding regions. It also serves as a baseline framework for future scientific research using the latest state-of-art machine learning tools for processing remote sensing data.

1. Introduction

Remote sensing is that the acquisition of data regarding associate degree about an object or development while not creates physical contact with the article and so in distinction to on-site observation, particularly the world. Remote sensing is employed in several fields, including land measure and as well as earth science discipline it conjointly also has military, intelligence, commercial, economic, planning . In the term “remote sensing” usually refers to the utilization of satellite- or aircraft-based detector technologies to employment and classifies objects on Earth, consist of on the surface and within the atmosphere and oceans, based on propagated signals. It classified into “active" remote sensing and "passive" remote sensing.

A soil may be a distinct ecosystem that is flooded by water, either for good or seasonally, wherever oxygen-free processes prevail. The primary factor that distinguishes wetlands from other land forms or Water bodies are the characteristic vegetation of aquatic plants, adapted to the unique hydric soil. Wetlands play a number of functions, including water purification, water storage, processing of carbon and other nutrients, stabilization of shorelines, and support of plants and animals. Wetlands are thought of the foremost biologically numerous of all ecosystems, serving as home to a wide range of plant and animal life. Whether any individual wetland performs these functions, and the degree to which it performs them, depends on characteristics of that wetland and the lands and waters near it. Methods for quickly assess these functions, soil ecological health, and universal wetland situation have been developed in many regions and have contribute to wetland conservation partly by raising public alertness of the functions and also the system services some wetlands give. Wetlands occur naturally on each continent. The main wetland types are swamp, marsh, bog, and fen; sub-types include mangrove forest, floodplains, mire, vernal pool, sink, and many others. The water in wetlands is either freshwater, brackish, or saltwater. Wetlands may be periodic event (inundated by tides) or non-tidal. Despite vital enhancement in remote sensing tools in each satellite image and applied techniques, the classification of complicated heterogeneous land cowl like soil is difficult. This is because, in a highly fragmented landscape, such as wetland, there are several small classes without a clear-cut border between them, which in turn, increases the within-class variability and decreases between class separability. Further- more, some of these classes may have very similar spectral characteristics, which further complicate the matter. Thus, incorporating the spatial feature within spectral information may contribute to differentiating complex land cover. Several approaches have been proposed in order to evaluate the efficiency of integrating spectral spatial features for classification, including kernel methods, In particular, deep learning is one of the most well known approaches to obtain high level spatial features using a hierarchical learning framework. It works based on a multilayer interconnected neural network framework that learns features and classifier simultaneously. This is also known as an end-to-end feature learning framework, wherein the image pixels and semantic labels are input and output of the algorithm, respectively. Convolutional neural network (CNN) is one of the most efficient approaches among all deep-learning-based frameworks that does not require prior feature extraction and thereby has a greater generalization capability. This is because a multilayer-based classifier has a high capacity to exploit abstract and invariable features. In specific, a deep CNN extracts the varying level of abstraction for the data in different layers. It obtained in the initial, intermediate, and last layers, respectively. There are three main strategies to use CNN, including full training, fine-tuning, and pertaining CNN .In a fully trained CNN, a network is built from scratch in order to extract particular visual features based on the applied dataset. Despite the great efficiency and robustness of this method, which provides a full control over the parameters and architecture, this is in- appropriate for remote sensing applications. This is because building a network from scratch requires a large amount of training data. The other two approaches are represented as more promising for remote sensing applications since they utilize the pre-trained model, which has been previously trained using different data. This is possible because the initial layers of CNN are typically general filters (i.e., low-level features such as edges); therefore, they need a little or no update during the fine-tuning process. The efficiency of deep CNN has been demonstrated in object detection, recognition of handwritten characters and traffic signs and classification. Although the application of CNN was employed in a number of remote sensing studies for classification of different land cover types using hyper spectral imagery, its efficiency was not examined for complicated land cowl classification (e.g., wetland and sea ice). Currently, the classification of the complex land cover is performed by incorporating a large number of input features to address the difficulty of discriminating land cover classes with very similar spectral signatures. However, extracting an oversized variety of input options Is not time economical, while their manipulation could be challenging. Furthermore, a number these input options area unit extremely related to features are highly correlated, which means no improvement in the in- formation content of data. Accordingly large variety of feature choice algorithms are proposed to deter- mine optimum features for different applications.

2. Methods

2.1Study Area and Dataset

The study area is located Cambodia, Phillippine, South Australia. In order to leverage various spectral and flooding information contained in satellite images, the above-described bands will be used in our flood detection. In our work, satellite images are downloaded from the USGS website, which is mainly selected according to different flood coverage and the underlying surface. According to the needs of the subsequent experiment, dataset from different regions taken as satellite images need to be divided into a test set and a training set. Its sensors have 5-m spatial resolution with five different spectral bands: blue, green, red, red-edge, and near-infrared.

2.2 Convolutional Neural Network

The "fully-connectedness" of these networks makes them to over fitting data. CNNs take a different approach towards regularization they take advantage of the hierarchical pattern in data and bring together more complex patterns using small and simple patterns. Multilayer perceptrons is a fully connected networks, each neuron in one layer is connected to all neurons in the next layer. Therefore, CNN is a scale of connectedness and complexity are on the lower extreme.CNN is one of the most well-known deep learning algorithms, and has gained interest for image processing in recent years.CNN is superior to other deep network algorithms due to it stability to preserve the geometry of the image(i.e.,the2-Dformat). Particularly, it maintain the inter connection between pixels and accordingly, preserves the spatial information. A typical CNN network consists of three types of layers, namely the convolution layer, the pooling layer, and the fully connected layer. The convolution layers extract information from previous layers and acts as a filter in the image domain. The filter's values also determine the type of information to be extracted. This filter is sensitive to the spatial information and is defined as a rectangular grid inside the layer. This layer is formulated as a simple convolution.

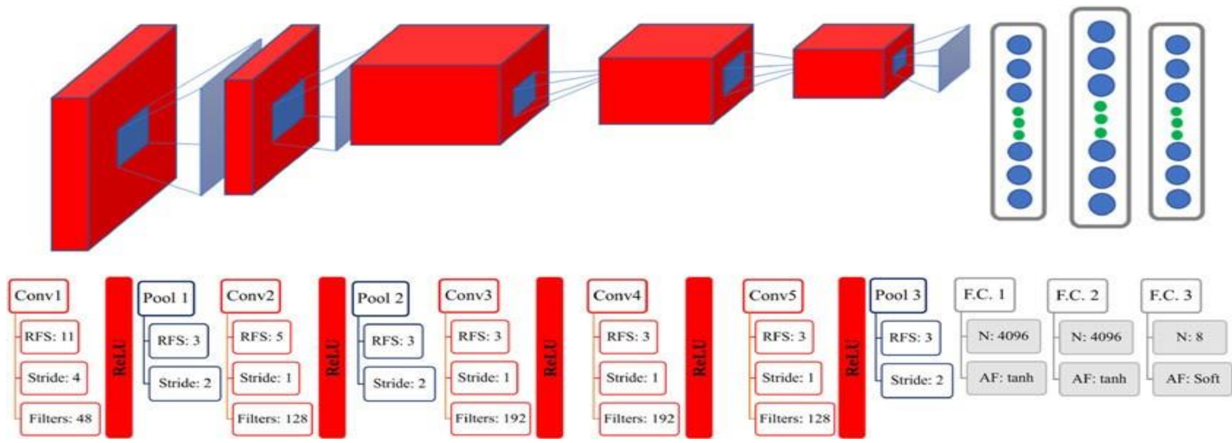


Figure1:Architecture of AlexNet employed in this study (Conv: convolution layer, Pool: pooling layer, F.C.:fully connected layer, RFS: receptive field size,N: number of neurons in fully connected layer, AF: activation function, Soft:Softmax).

$$\textbf{Feature map} = \textbf{input} \ast \textbf{kernal}$$

The second layer, the called pooling layer, reduces the size of data and it preserves the most important information and the geometry of the input data. In each pooling layer, a particular number is determined by sub sampling of a small selected rectangle. There are different methods for sub sampling such as using maximum value or a linear combination. The last layer namely the fully connected layer, is the reasoning part of the network, which determines the final label of the input data. Particularly, each neuron receives the information from all neurons in the previous layers to make the final decision.

2.3 Preprocessing Step

A comparison of spectral characteristics of four flooding regions was carried out by plotting their signature using 1000 samples. First, the spectral signature of these flooding regions follows a very similar trend. Second layer, classes in different bands covers a wide range on these 1000 samples.

This means that these flood detection have a high standard deviation resulting in a wide overlap between them. Accordingly, the high degree of misclassification would occur in case of exclusive use of spectral information into the classification scheme. Thus, it was concluded that the spectral characteristics of the Cambodia, Philippine, South Australia. A band selection technique was employed to reduce the dimensionality of the input data.

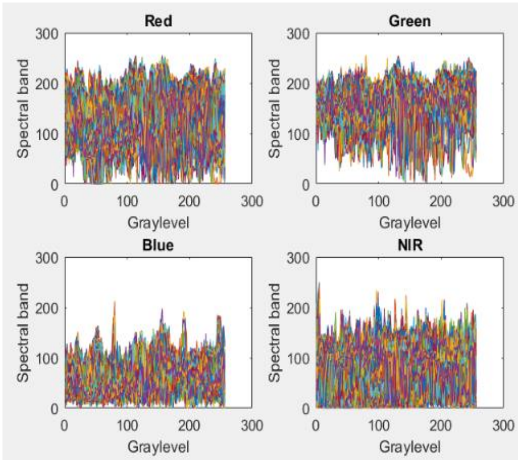


Figure 2: Spectral signature of flooding in Cambodia

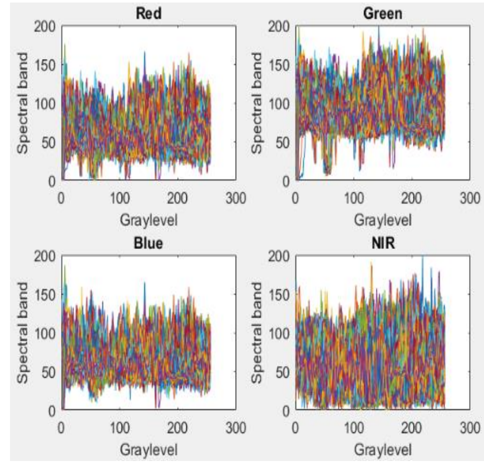


Fig.3 Spectral signature of flooding in philippine

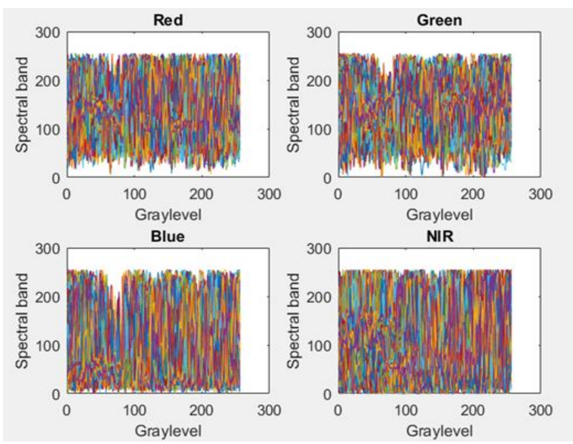


Figure 4: Spectral signature of flooding in South Australia

2.4 Training step

The main challenges related with the network training were the limited number of training samples and determining an optimal patch size to be utilize in PBIL. Instead of full training a network from scratch, a pre trained network can be utilized, which addresses the former problem. In this approach, the parameters of the last layers are mostly updated, not those of all layers. Furthermore, the updates values are small since the updating is carried out on a pre trained network. Due to the limited number of in-situation this study, the last four layers of the network were updated to ensure a sufficient amount of sampling data for both training and testing the networks. However, ancient details from the image, such as the size of substance of interest and the network architecture, is required in order to concentrate on the latter difficulty. In particular, each patch should have enough information to generate a distinct distribution for the specific object within the image. Different patch sizes were tested according to spatial resolution of the data and object size of interest from 10 to 40. A patch size of 30 found to be an optimum value in this study because a small patch size resulted in over fitting of the model, and on the other hand, under segmentation was observed in the case of a large patch size.

2.5 Testing step

In order to evaluate the robustness of the CNN result and to prevent information leak from the testing data set to the model, two strategies were considered during test data preparation .First, to make sure that the testing data set is independent of the training dataset and both group shad roughly comparable pixel counts ,reference polygons in each class were sorted based on their size and alternating assigned to testing and training groups. This procedure ensured that both the testing and training groups are selected independently from different parts of the image. Second, to make sure that the network is not over fitted, the model was trained over first satellite imagery and accuracy indices were determined based on classified map, which was obtained by applying the trained model over the second satellite imagery. Since the second image was acquired on a different date and was spectrally different from the first image, this procedure illustrates the reliability of results on the testing dataset. It also compared the result of CNN with a state-of-the-art classifier ,random forest(RF).More specifically, the two main parameters of RF, which should be adjusted, are the number of trees(Ntree) and the number of variables(Mtry). In this study, a total number of 500 trees were selected in classification model. Moreover, the square root of the number of input variables was considered as Mtry. This is because it decreased both the computational complexity of the model and the correlation between trees. However, a feature extraction step was an additional step, which is required in such a classifier before the classification step.

3. Results And Discussion

The training is actually a fine tuning of a pertained network. To have a better understanding of the features that were generated and used during the training phase, features of some random patches were extracted. Every patch is normalized and resized to feed the network. The designed convolution kernels are then applied to the input patch to generate some normalized features. Each feature highlights a group of similar objects. The kernels are designed to highlight the group of pixels that decrease the loss function. To evaluate the efficiency of CNN for wetland mapping, the classification results of CNN were compared with the RF classifier. An RF is an ensembles classifier and has shown good results for several lands cover mappings. For classification based on the RF classifier, a total number of eight features, namely normalized difference vegetation index (NDVI), normalized difference water region.

The training step was completed using 30, 000 iterations in approximately the speed of convergence is high in the initial epochs.

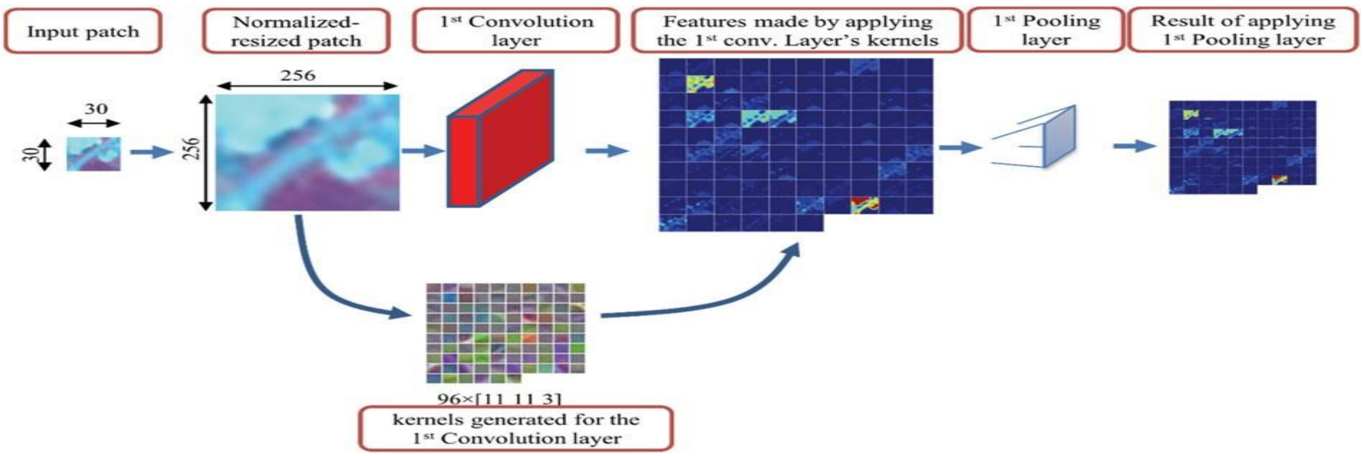
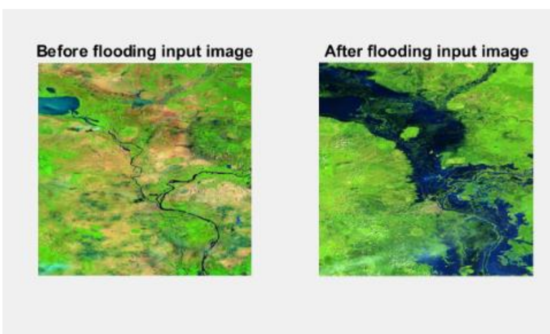


Figure 5: First convolution layer, its designed kernels, and generated features.



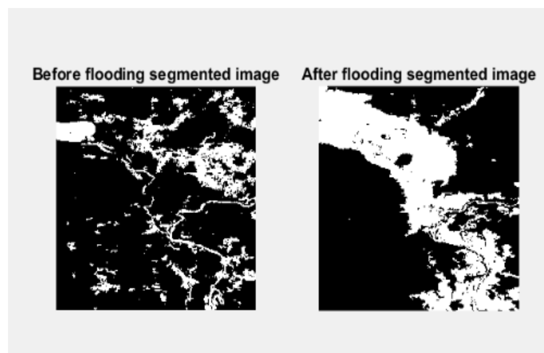
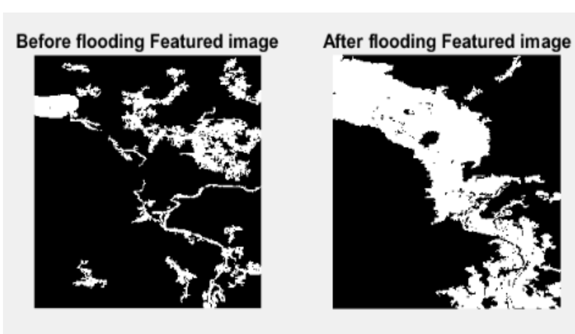


Figure 6: Input images of Cambodia.

Figure 7 : Before and after flooding segmentation



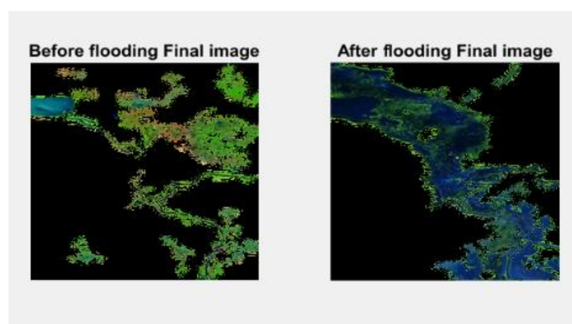


Figure 8: Featured images.

Figure 9: Before and after final flooding

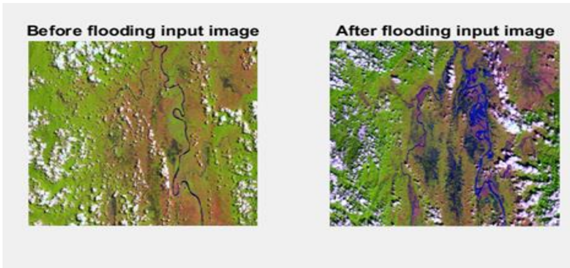


Figure10: Input images of Philippine.

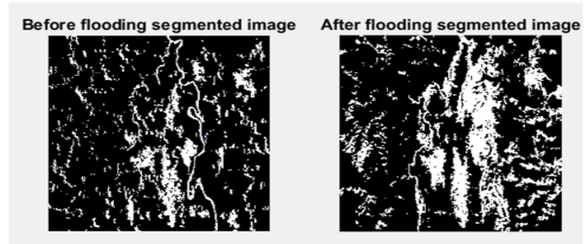


Figure 11: Before and after flooding segmentation

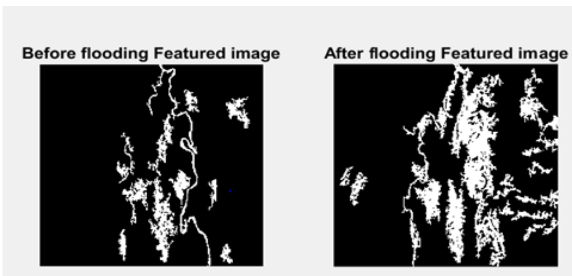


Figure 12: Featured images.

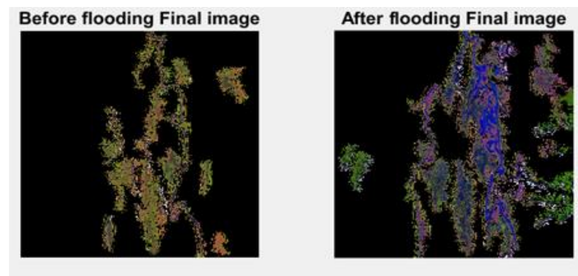


Figure 13: Before and after final flooding

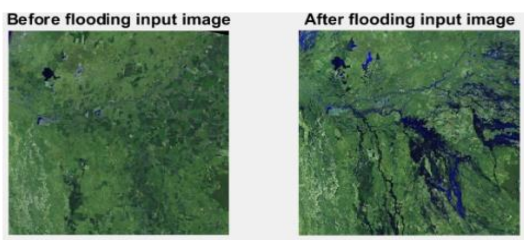


Figure 14: Input images of South Australia

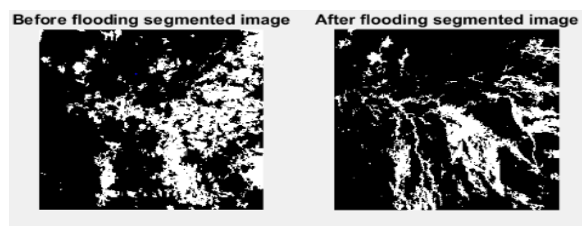


Figure 15: Before and after flooding segmentation

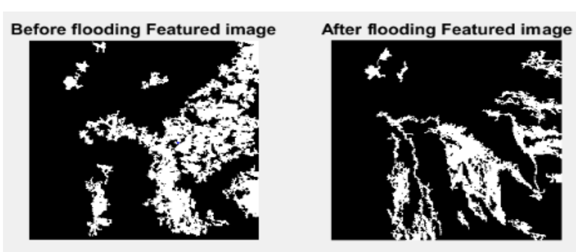


Figure 16: Featured images.

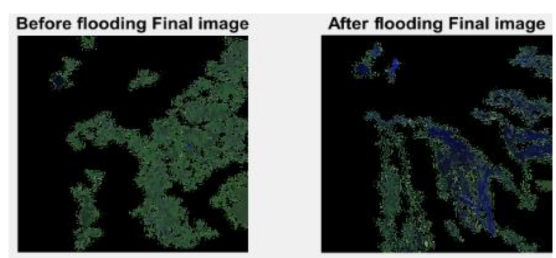


Figure 17: Before and after final flooding

4. Conclusion

The proposed system uses pre-existing CNN, namely Alex Net, for mapping flood detection using remote sensing images. The overall classification accuracy obtained by CNN, that was suggesting the superiority of CNN relative to segmentation of images even by incorporating a smaller number of input features. The later observation suggests the significance of incorporating high-level spatial features into the classification scheme to reduce confusion between spectrally similar flood classes. The novel classification framework, employed in this study, along with the fine spatial resolution mapping. Every patch is normalized and resized to feed the network. The designed convolution kernels are then applied to the input patch to generate some normalized features. Each feature highlights a group of similar objects. The kernels are designed to highlight the group of pixels that decrease the loss function. These high-level features mostly rely on the spatial information in the patches. In detection of wetland on flood affected regions using remote sensing images accuracy of 90.64% was employed. Furthermore, the use of other very deep CNNs, such as DenseNet, VGG, Xception, and Inception ResNet for classifying wetland complexes offers a potential avenue for further researches.

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