Less is More when Applying Transfer Learning to Multi-Spectral Data

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Abstract. Transfer Learning is widely recognized as providing incredible benefits to many image processing tasks. But not all problems in the computer vision field are driven by traditional Red, Green, and Blue (RGB) imagery as tend to be assumed by most large pre-trained models for Transfer Learning. Satellite based remote sensing applications for example typically use multispectral bands of light. While transferring RGB features to this non-RGB domain has been shown to generally give higher accuracy than training from scratch, the question remains whether a more suitable fine tuned method can be found. Given this challenge, this paper presents a study in multispectral image analysis using multiple methods to achieve feature transfer. Specifically, we train and compare two pre-trained models based on the Resnet50 architecture and apply them to a multi-spectral image processing task. The key difference between the two models is that one was pre-trained in a conventional way against RGB data, while the other was trained against a single band greyscale variant of the same data. Our results demonstrate an improved performance on the greyscale pre-trained model relative to the more traditional RGB model.

Keywords: Deep learning · Transfer learning · Image Analysis · Resnet · CNN · Multispectral images · ImageNet · Satellite imagery · EuroSat.

1 Introduction

The rapid advancement of artificial intelligence (AI) in the computer vision field has increased the demand of large-scale labelled data. AI has enabled organisations to look towards Earth Observation (EO) or Remote Sensing (RS) for collecting information on buildings, natural structures, urban and rural boundaries, as well as for prediction and estimation of natural calamities, forest fires, melting glaciers, vanishing forest covers, and monitoring humanitarian crisis. Satellite image classification has many challenges too, like high variability, small size of labelled datasets, low spatial resolution, and the multispectral nature of images. Normalization of satellite images is also not easy, mainly due to the presence of clouds in EO images, or due to prevailing weather conditions, or due to the changes in lighting of an area at different times during a year. All these issues make creation of a large labelled EO dataset very difficult. EuroSat and SpaceNet [1] datasets have tried solving the problem of small labelled datasets. Other approaches are, unsupervised feature extraction from an image [2], using large RGB-trained networks like VGG16 for transfer learning [3], and lastly training Convolutional Neural Network (CNN) from scratch over small available labelled data.

Attempts have been made to transfer features learned in ImageNet classification problems to the smaller target satellite imaging domains. There are some key differences between natural image domain of ImageNet and RS domains, like, objects are very small in satellite imagery, and moreover these images are multispectral in nature meaning an image has multiple frequency channels summarized in it. A lot of information is stored in an RS image than a typical RGB image. Since these two domains are primarily of different nature, accuracies achieved are either not in very high ranges or results are not reproducible. Arguably the primary reason for this is that images taken by satellite are multispectral in nature, meaning they have multiple bands representing an image, other than just RGB or visible bands.

Doing transfer learning, using a model pre-trained on RGB (coloured) images, is arguably not the right approach when your target dataset consists of multispectral or images with multiple bands. State of the art solutions transfer ImageNet RGB features to multispectral domains, even for single channel grey-scale domains like medical Imaging [4]. Multispectral images and natural images are extremely different to one another, so any meaningful transfer is highly doubtful. It is also observed that the usefulness of a pre-trained network increasingly decreases as the task the network is trained on moves away from the target task [5].

Given the above, this work hypothesizes that a large CNN trained on single channel images, can learn more relevant features for multispectral image analysis, than the one trained on coloured images. This might seem counter-intuitive at first a pre-trained RGB model would be assumed to learn more features than a similarly structured model that is trained on only one channel. However, we argue that the fact that 3 particular channels and their colour based inter-dependencies introduce a bias in the pre-trained model that is not met by the multi-spectral target domain where multiple different channels are available. While the ideal case would be to have a pre-trained model on full-multispectral information that is the exact same number of channels as the target domain, this is not yet a reality. We argue that a compromise is to apply a pre-trained model to each individual channel in a multi-spectral model, but to make sure that the pre-trained model is optimised to provide useful features for single channel analysis.

To be more concrete, this research approaches the problem of classifying a multispectral image, by firstly training a large network, Resnet50, on a single channel image dataset, and then use this large network to transfer features to the target domain of multispectral image classification. We compare this approach to a more traditional configuration where the Resnet50 model is pre-trained with

RGB data. We proceed with a short review of relevant literature before detailing our experimental methodology and results.

2 Literature Review

CNNs are the default in handling image data. ImageNet Large Scale Visual Recognition Challenge (ILSVRC) is an annual image classification and detection competition on large natural image database [6]. ResNet [7] has won ILSVRC in 2015. ResNet was truly deep network with 152 layers in it and is one of the fastest, most widely used and accepted ImageNet trained model. ResNet handled problems of vanishing and exploding gradient, which crops up as a network grows deeper by using *Residual Blocks* in the network which are combination of conv-relu-conv series and allowing skip connections between these blocks. During back propagation, gradient flows easily through the network without getting lost or very weak.

If the dataset is smaller, we cannot simply apply bigger and bigger networks as was the case for the ImageNet challenge; instead, we need to apply another technique. One such way to get good accuracy is called the Transfer learning ([8–11]). Large neural networks trained on large image datasets like ImageNet have shown that network's first few layers learns features similar to Gabor filters. These initial layers carry information like what are the location of edges, boundaries, corners, and shapes present inside an image.

These features or information contained in the initial layers are not specific for any task. They are general in nature and are applicable to all sorts of target images and tasks [5]. In this landmark paper, authors established some of the key concepts of transfer learning like – features transition from general to specific from first few layers to final few layers, features are not highly transferable to a distant target task, and lastly any kind of transfer is better than random initialization even when the source and target tasks are not that similar. Generally, the target task is much smaller than the source task. Transfer learning is of two types – One in which pretrained features or the features learned from the source are not touched or are frozen and only new layers are trained on the smaller target task, second in which some or all source layers are allowed to train on target task or their learned weights are allowed to be fine-tuned.

Models pretrained on ImageNet have given great results in transfer learning, both in supervised and unsupervised domains ([12–14]), these papers further established that large CNN networks have the intrinsic capabilities of learning general transferable features. Further efforts have been put in to understand how neural networks are able to generalize so well and how to make them more robust ([15, 16]).

Small labelled datasets can also practice data augmentation to increase the dataset size and thus improve the model fitting over the data [17]. This problem is especially common in a multispectral domain like satellite imaging. Data Augmentation also helps in reducing overfitting. It helps in increasing the dataset size by either warping or oversampling the data while making sure that labels are preserved. General form of image augmentation includes data warping techniques of geometric and color transformations, like obtaining a new image by cropping, flipping, sheering, or inverting an image [18]. Augmentation in computer vision problems has been happening over the last couple of decades and was first seen in [19].

EO or RS has received attention from researchers around the world very recently. The data from these domains has the capability of bringing about significant improvements in agriculture. Use of RGB and Near-Infrared region images captured by low-orbit observational systems in estimating produce and mapping the plantation areas has been advocated as best practises [20]. Researchers have also used satellite images in detecting the sections of roads and urban areas covered under flood waters [21], and there are many more applications of satellite data like these two.

The problem with these EO datasets is that firstly, there are very few and very small sized labelled datasets available and secondly, image features in these datasets are quite different from those from natural image datasets, which have images like cat, dog, fish, scorpion, car, truck, house, ship and so on. UCMerced, for examples is a popular dataset of Satellite imaging [26]. It is a fairly small dataset with 21 land-cover classes, 100 RGB images per class, and 256*256 pixel dimensions. Likewise, the other datasets in use too have images in the few hundreds for every class label. In a supervised problem-solving approach, the performance of a classifier depends on the size and quality of a suitably labelled dataset. [12] suggested in their paper that deep networks learn features that can be treated at par or even better than the traditional manual methods used in computer vision. Thus, several attempts have been made using pretrained deep models to learn features in multispectral RS data [22–25]. All these studies have performed classification upon RS datasets, using ImageNet trained large deep networks.

3 Methodology

The purpose of this research is to test whether single channel features are better than RGB-features for models which are trying to learn multispectral data. This research suggests using greyscale pre-training rather than colour (RGB) to try to improve classification results on multispectral satellite data.

To achieve this we assumed a set of RGB images that are combined from mini-Imagenet and EuroSat datasets. For single channel features, greyscale variants (single channel) of these images were created. These greyscale images are the same as the RGB ones, except they are converted to greyscale using image augmentation methods prior to the training process. Multispectral data consists of satellite captured multiple band images. The dataset that the study uses has TIFF images consisting of thirteen spectral bands each. Six single bands are extracted from these .tiff images. Experiments are conducted using the ResNet50 network, which has a CNN as its main building block.

There are two sources of RGB and Greyscale images, one is the mini-ImageNet dataset and another one is the EuroSat dataset. Our design Methodology is such that first new models are created using Resnet50 architecture by training them from scratch over datasets from our two color spaces, namely RGB and Greyscale. Also note that, there are two types of datasets in each category, one is smaller in size and consists of Non-Augmented images, while the other one is larger and consists of Augmented images. So, four Resnet50 architecture-based models were created by training from scratch on RGB and Greyscale datasets independently. These four pre-trained models are then used to transfer features or are finetuned on target images of individual bands, i.e. band B02, B03, B04, B05, B08 band B12. The performance is recorded on test sets and a comparative analysis is made on the outcomes. This will make it four sets of test accuracies and F1 scores; two are for RGB based feature transfer and another two for Greyscale or single channel-based feature transfer.

4 Experimental Details

4.1 Data

The experiments are conducted using multiple sets of images, where each set has distinctive features and are as per the design of research.

The first dataset we make use of is mini-Imagenet. ImageNet itself is a large scale ontologically organised catalogue of images built upon the backbone of the WordNet structure. ImageNet consists of approximately 3.2 million images in total [6]. Due to the limitations of time and computational power for this particular study, a very small subset of this dataset, mini-ImageNet, is used for the purpose of this study. It has 500 images each in its 100 overall classes, and each image is of the height 64 pixels and width 64 pixels.

While mini-ImageNet provides the backbone dataset for pre-training we also require a target domain dataset. For this purpose we use the EuroSat dataset. The EuroSat dataset contains two sets of images - namely RGB and Multi-spectral imagery. There are around twenty-seven thousand images in 10-classes, collected by the Sentinel 2A satellite. Classes are different land-use types for example, Residential, Industrial, Farmland, Rivers etc [21].

Given that mini-ImageNet contains only five hundred images in each class, we apply data augmentation to increase the size of the dataset to two thousand images in each class. Data augmentation is done using basic geometric transformations like shifting the image across its width and height, shearing or tilting the image along one of the axis, zooming in and out of the images, flipping the image either horizontally, and lastly by rotating the images by not more than 90 degrees at a time.

For every augmented and non-augmented image an equivalent greyscale version is created. The images in RGB and Greyscale set are exactly same. Here greyscale is used to represent the idea of single channel and these images will be used to train Resnet50 based network from scratch, to prepare a single channel trained classifier. This will later be used for transferring features to target domains of multispectral bands. It should be noted that our greyscale images were not constructed by arbitrarily deciding upon a single band from the input RGB image, but rather through the application of an RGB to greyscale transform.

There are ten classes in the EuroSat data, for both RGB as well as Multi-spectral images. Please refer figure 1 to see the extracted images for all 13 bands and the sample image.

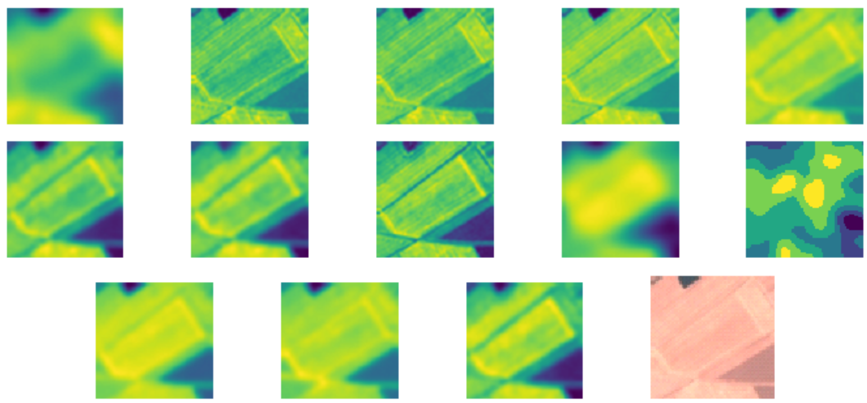

Fig. 1. Same image extracted as 13 Bands. From left to Right, and top to Bottom - Band01, Band02, Band03, Band04, Band05, Band06, Band07, Band08, Band09, Band10, Band01, Band11, Band12, Band13, and lastly the Original RGB Image.

4.2 Implementation

Model Architecture Our backbone model architecture is based a Tensorflow / Keras implementation of Resnet50 – a fifty-layer deep neural network. For the prediction network sequential TensorFlow Keras layers are added to the backbone network.

For initial training, Resnet50 is used with random weight initialization, and its layers are kept as trainable. Also, the top layer is replaced with a fully connected layer with number of nodes equal to 110 or the number of target classes (100 ImageNet classes and 10 Eurosat classes). This model is trained from scratch on the combined dataset of mini-ImageNet and EuroSat, once on RGB (RGB Model) and then on Greyscale (Greyscale Model) colour spaces. For the Greyscale model, single channel goes in as input to the three-channel input of the base model Resnet50. On top of trainable Resnet50 base-model, one fully connected ReLU layer with 256 activation nodes is added. This layer is followed and preceded by a Dropout layer with dropout nodes set as 0.5.

RGB Model and Greyscale Model are used to transfer learned features to Multispectral feature space separately. A new network is designed and is used in place of the top layer of the base models A and B for this purpose. This network consists of one fully connected dense layer with Sigmoid activation function,

followed by a dropout layer and lastly the final output Softmax layer with 10 nodes. Model architecture is same for all the six bands. These bands are chosen out of given thirteen bands because of two main reasons – they were the top performers in the original paper as well [21], and some of the bands (B01, B09, B10 and B11) are not meant for land observation altogether. Thus, the Bands that will be evaluated in this study are –
Band02 – Blue Color
Band03 – Green Color
Band04 – Red Color
Band05 – Red Edge 1
Band08 – Near Infrared
Band12 – Shortwave Infrared 2

Transfer Learning The premise of Transfer Learning is that our pre-trained networks (RGB Model and Greyscale Model) contain a rich set of descriptors or filters. To use the concept of Transfer Learning effectively, features learned from previous task of training over mini-ImageNet and EuroSat are transferred to the target task of Multispectral nature in some series of steps. This is achieved by using "Fine-Tuning" techniques. Learned filters are reused by training the network in parts. The network's architecture can be understood easily from the figure 2. The steps that this research has followed are as follows –

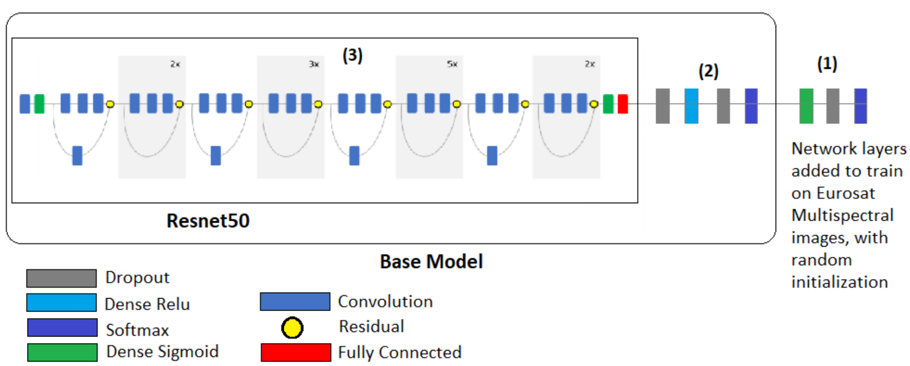

Fig. 2. Final network architecture. Resnet50 is used as a building block for creating the Base Model. This model has been trained on RGB and Greyscale images separately. Later on, this Base Model is used for transferring features learned to the target task. Figure shows Different steps in Fine-Tuning and Feature Transfer.

– Step 1 – Train only the head of the network or the new network layers that have been added to the base-model and keep the rest of the layers as frozen or non-trainable. In the figure 2, the section marked as (1) is the new network

added on top of the Base Model. Thus, section marked as (2) and (3) are kept as non-trainable. The fully connected layers in section (1) are initialised with random weights and trained over the EuroSat single band images extracted from the multispectral .tif images. Reasoning – This way only a part of the network is being trained at first and the weights correction is not back propagated into the entire network. If the whole network is allowed to train from scratch on the target data, there is a risk of losing the features and filters learned by the fully trained base model. This training is done only for a few epochs (number of epochs = 5), so that the final layers can learn requisite number of features or patterns on the target data.
- Step 2 – Train only the non-convolutional layers in the Base Model, and no weight update will happen for the Resnet50 layers, i.e. the section (1) and section (2) layers as shown in the figure 2. In step 1 and step 2, the network is being warmed up for the task at hand.
- Step 3 – Unfreezing the last residual or convolutional block in the Resnet50 layers. This is the terminal block in the section (3) of figure 2. The network is fine-tuned or trained over the target data for larger epochs.

5 Results

We first present the results of the pre-training process before detailing the specific results for the target EO data in more detail.

5.1 Base Models

The performance in land-cover classification task is taken as a measure to answer the research question. Two similar models are trained separately on non-augmented RGB and Greyscale images. The number of training images per class is low. Two other similar models are trained separately on the larger (four times size) database of augmented RGB and Greyscale images. For all these four models, a high training accuracy, in late 90%s, has been achieved by training just over 100 epochs. However, the validation scores were low due to large network size, smaller training data, and processing limitations. Nonetheless, these *base models* have learned a lot of transferable features from their respective color spaces at the end of this *base model* training.

5.2 Model on Band B02, B03, B04, B05, B08, and B12

The model architecture for all bands are identical and already discussed. In total, twenty-four models were created over six training sets belonging to six different bands. Table 1 below, shows overall accuracy values over test sets for these six bands, where AUG stands for base models created over larger augmented datasets. It is evident from the table that for all bands the highest accuracy was recorded when Greyscale Augmented data was used to train the base model. Further note that for five out of six bands, the Greyscale base model has trumped the RGB base model. The grouped bar charts, shown in figure 3, clearly depicts the behaviour for all bands over different base models. On an average, the performance was worse when RGB images were used to train the base model, and it was best when Greyscale images were used for training of the base model. Also, note that augmentation helped in increasing the performance in both cases – RGB and Greyscale. Data augmentation created a huge difference in base model's capability to transfer general or relatable features.

Table 1. Accuracy values over the dataset for different bands as measured for every Base-Model.

Bands	**RGB**	**GREY**	**RGB-AUG**	**GREY-AUG**
Band B02 – Blue	57.7	60.67	59.87	66.3
Band B03 – Green	54.82	56.19	61.27	65.83
Band B04 – Red	55.02	59.62	59.71	62.6
Band B05 – Red Edge 1	43.44	43.32	45.44	52.78
Band B08 – NIR	55.82	58.84	59.64	64.05
Band B12 – SWIR 2	43.11	45.15	47.29	54.35

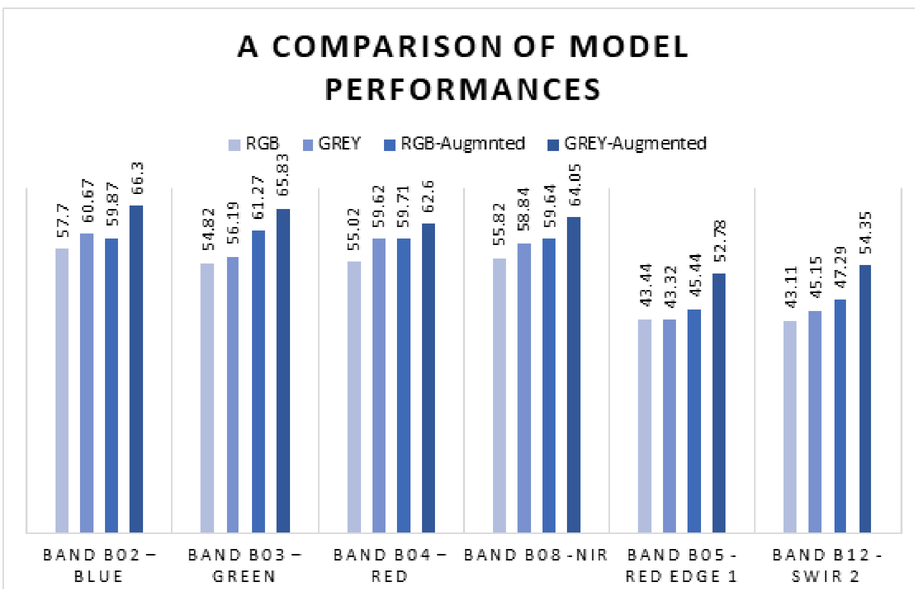

Fig. 3. Grouped bar charts depicting the performance of different bands as well as different base models among them. Clearly Greyscale Augmented base model has outperformed in every group.

Model Band B02 For all the bands Precision, Recall, and F1 Scores were plotted for performance of Grey-trained, RGB-trained base models in both, augmented and non-augmented space. Figure 4 shows classification performance for Band B02, when Grey-trained base model was used to transfer features. it can be seen that, classes Sea Lake, Residential, and Forest have given the highest F1 scores, while Highway, River and Permanent Crop are the lowest performing classes. High Precision, Recall and thus high F1 score for class Sea Lake can be explained by the fact that a water body has entirely different reflectance values from another typical land bodies. For all bands and across all types of base-models, similar trend was seen.

Further Generalisation While our initial approach here did assume a baseline model built out of both ImageNet and EuroSAT RGB data – resulting in a 110 class dataset, we recognise that this would perhaps not be the most generalised of baseline models. While it is a smaller dataset, we also ran the above experiments with a more basic setup while using only mini-Imagenet data for the base model training – there was no EuroSat data in the base model. Again this approach demonstrated that a greyscale based baseline model outperformed the RGB base model, please see Table 2 on page 11.

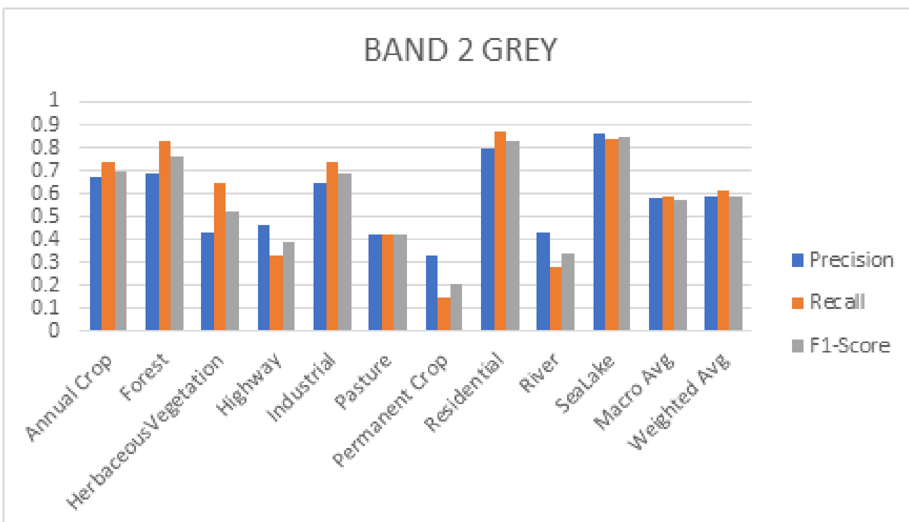

Fig. 4. Comparative performances for Greyscale images trained base model.

6 Conclusions and Future Work

This research aims to improve the transfer-ability of large CNN models to target domains of single or multi-channel images having small labelled datasets like domains of RS and Medical Imagining. Our results have shown that single channel trained base models are better at transferring relevant features to a multispectral problem space like that of RS, in comparison to RGB trained base models. Using this knowledge, better RS applications can be developed. Many RS fields stand benefitted from this research like flood detection, coastline detection, urban and rural planning, and also military research.

Table 2. Accuracy values for bands for every Base-Model trained only on mini-ImageNet dataset.

Bands	**RGB**	**GREY**
Band B02 – Blue	58.79	63.34
Band B03 – Green	56.57	58.68
Band B04 – Red	57.64	60.96
Band B05 – Red Edge 1	44.71	44.87
Band B08 – NIR	57.06	60.84
Band B12 – SWIR 2	45.01	44.38

Future work and Recommendations Using the base models created during the research, similar analysis can be conducted on some band combinations as well. One important future work that will be taken up is, using the full ImageNet dataset for training the base model. We believe this model will provide better results again – particularly if combined with a more complex state-of-the-art image network than the Resnet50 we have applied here. We believe that these two elements taken together, with a more generalised set of testing models, will underscore the usefulness of this contribution.

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