DOFA - Hot topics in Computer Vision

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Abstract

Large language models have shown impressive performance gains for various tasks in language processing over the last few years. It is reasonable to think that some of the problems in remote sensing image processing, such as scarcity of labeled data, can be overcome with the help of foundational vision models.

*In this work, we provide an evaluation of the **DOFA** model when using the BigEarthNet dataset. This includes an analysis of the feature vectors, as well as different approaches for using these features in multi-label classification.*

We've seen reasonable performances across different metrics but no improvement compared to other models trained on BigEarthNet.

1. Introduction

The success of computer vision deep learning models relies heavily on the large amounts of data available for training on the internet [16]. In the domain of remote sensing, however, labeled data is hard to obtain because labeling is a complicated task that requires expert knowledge and there is a much wider range of sensors compared to standard RGB cameras of everyday cameras. [20]. There are multiple ways to address this issue, such as using synthetic data or semi-supervised learning algorithms. Following the breakthroughs of LLMs and the concept of pretraining foundation models on a wide range of tasks, recent research has attempted to transfer this concept to the area of remote sensing computer vision [2].

This report focuses on one foundational model called 'DOFA' [20] and evaluates it on a new downstream task for comparison with other foundation models. The used dataset is called BigEarthNet [15] and we will be utilizing the Sentinel-1 data. We will provide results using different metrics for the multi-label classification of both the 19-class and 43-class variants.

We will analyze the meaningfulness of the features computed by the DOFA model by applying a UMAP transformation [10]. Afterward, we will use the features as input data for training various classifiers on the classification task.

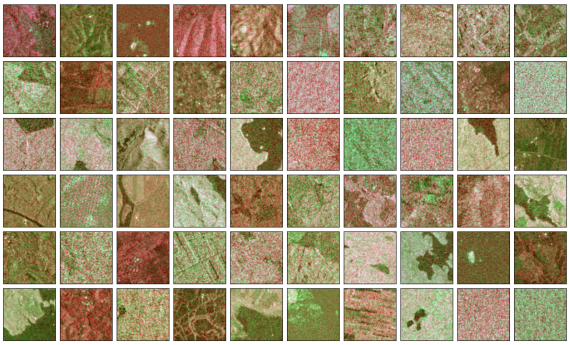

Figure 1. False color visualization of some images from Sentinel-I satellites as part of the BigEarthNet dataset [15]

2. Related research

Self-supervised learning has been used for several years to accomplish different tasks in remote sensing and is also applicable for training larger multi-modal foundational models [5, 6, 20]. There are two primary methods to generate meaningful features. The first method is to use contrastive learning [3], where two views of the same image should be close together in feature space, while two views of different images should be far apart from each other. These two views can be simple image transformations or, for example, the same area of the earth captured by a different sensor. There are many examples with different strategies for this contrastive learning approach [1, 5]. Research has shown that this approach tends to produce models that ignore information in the data that is not shared between the augmented views, regardless of whether this information would be useful in later downstream tasks [17]. Because of this, it is crucial to select an appropriate augmentation strategy as this decision heavily affects the performance of the

model [12].

The alternative to contrastive learning is learning to reconstruct images. An example of this approach is SimMIM [19]. These models can be easily scaled as they don't rely on image pairs [8], but they require additional fine-tuning to become useful for downstream tasks [9].

Most previous foundational models were trained on a single sensor type. For example, Scale-MAE [13] is for optical data, SatMAE [5] for Sentinel-2 data, and so on. Although these models can be used for various downstream tasks in their specific sensor domain, they can't generalize across these domains. According to DOFA, this leads to several limitations. Models are unable to utilize most of the unlabeled data during training because it is from a different sensor type. They also lack universality when the downstream task differs from the original data as needed channels and bandwidths change based on the used sensor. Overcoming these limitations and leveraging data from various sensors is the main goal of DOFA [20].

Various studies have attempted to address the issue of multi-modality, such as [6, 7, 18].

3. DOFA Model

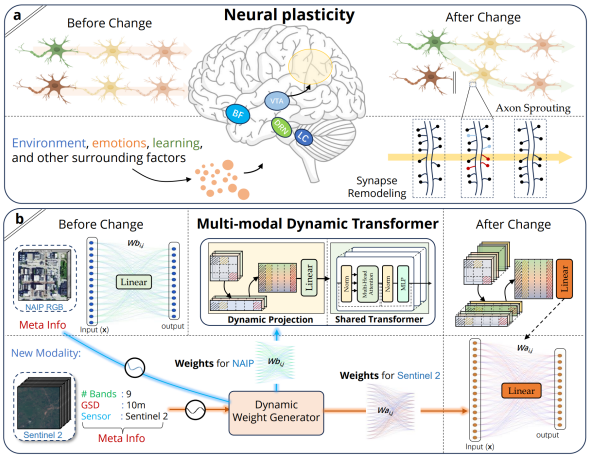

Figure 2. Visualization from the original paper [20]. Shows the inspiration for neural plasticity from the human brain and it's application for the DOFA architecture.

'DOFA' stands for *'Dynamic-One-For-All'* model, inspired by the concept of neural plasticity from brain science. The main goal is to integrate various data modalities into a single framework, adaptively adjusting to different sensor inputs without needing separate models for each sensor type. This means that the model adjusts weights based on the varying wavelengths of the input data. The training process resembles that of a single large transformer model.

The authors used data from *different sources and sensors* including Landsat, Sentinels, MODIS, EnMAP, Gaofen, and NAIP, which are representative of a large range of spectral bands, resolutions, and imaging types. DOFA is trained using masked images and predicting the missing patches to learn meaningful representations on unlabeled data. It uses *pre-trained models* that were trained on ImageNet to enhance training efficiency and reduce training times. Additionally, as a new distillation loss is introduced to improve model performance.

The *distillation loss* is derived from the concept of knowledge distillation, where we want to transfer knowledge from a larger model (e.g., trained on ImageNet), which we call the 'teacher' model to a smaller model which we call the 'student' model. The basic idea is that the student model (DOFA) is trained so that its output aligns closer to that of the teacher model. This is especially useful when it comes to data that the teacher model has already seen, which in this case refers to RGB images (for example on landscape images which are somewhat similar to remote sensing data). This setup should accelerate training convergence and enhance the overall performance. This loss is combined with the loss for image reconstruction. Together they guide the model to not only reproduce the input data correctly but also form representations that are informed by the teacher model.

The core idea of adjusting weights is through a second *hypernetwork*. This secondary neural network is trained to generate weights and biases for the main network (transformer-based) to execute, based on the input data.The characteristics utilized include central wavelengths associated with each input band and their standard deviations. The hypernetwork learns during training to generate effective weights as it receives feedback on the performance of the primary network. This approach makes it possible to use tailored transformations for different modalities *and* train everything in one go. The whole architecture is shown in Figure 2.

The authors claim that this approach using one foundational model *reduces the computational overhead* and complexity compared to multiple specialized models. Through its multimodal training, the model should be able to handle EO tasks and data types that it hasn't seen before. This concept of multi-modality is expected to be transferable to other fields like medical image analysis and robotics.

The results in their paper show high performances in different datasets and downstream tasks compared to other approaches. The only dataset in their evaluation that is behind other approaches is the BigEarthNet for which we will provide more results.

[20]

4. Methodology

The images from BigEarthNet are fed through the DOFA model, and the resulting feature vectors are used for further analysis, such as UMAP visualization and as training data for downstream tasks. The approach relies on PyTorch (for DOFA execution and classifier training), scikit-learn (for classifier training and metrics), and a Python implementation of UMAP.

5. Experiments

5.1. Data

We're using the *BigEarthNet dataset* [15] for our evaluations. The goal is to use the model as a feature generator and leverage these features to solve the multilabel classification problem for both 19 and 43 classes from BigEarthNet. This dataset contains around 550,000 image patches from Sentinel-I and Sentinel-II, each labeled with multiple classes. We are going to use the *Sentinel-I* images for our experiments.

The data is split into train and test sets based on the implementation from the torchgeo repository. The train dataset contains around 270,000 and the test dataset has 125,000 images.

There are significant differences in the occurrence of certain classes in the dataset (see Fig. 3). There are, for example, only a few images with wetlands, beaches, and moors. The metrics during the evaluation must account for this.

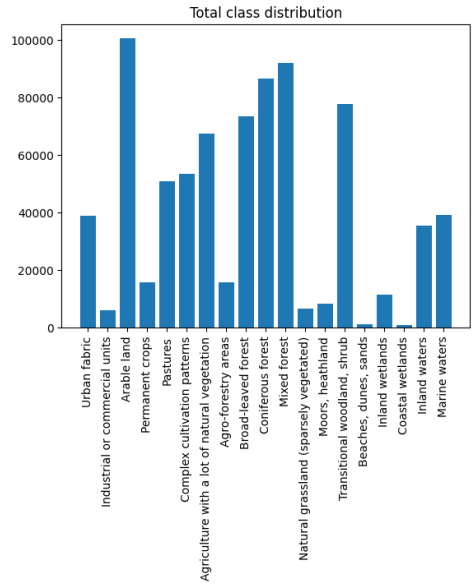

Figure 3. Distribution of the classes in the train dataset. This is a multiclass dataset so one can have multiple classes.

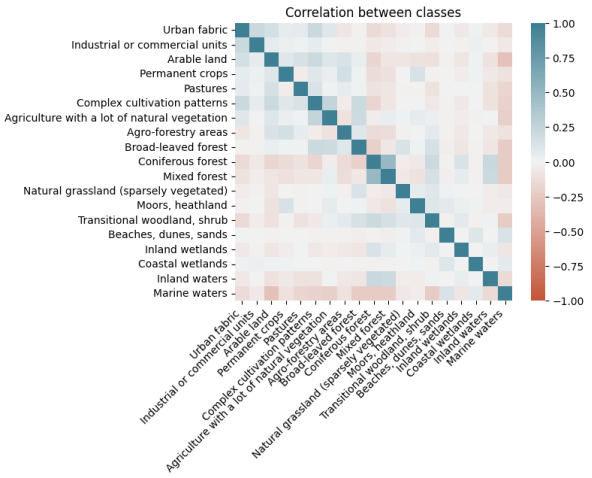

Figure 4. Correlation of classes in the train dataset (19 classes) - We see low correlation between most of the classes. There are some exceptions, e.g. Marine waters are negatively correlated with most of the other classes. We can expect higher performance for that class.

We analyzed the correlation between classes of BigEarthNet and the results are displayed in Fig. 4. The classes are mostly uncorrelated, with some exceptions, such as the high likelihood that coniferous forests are also mixed forests, and that marine waters are usually not present in the same images as other vegetation forms. Due to that analysis, we can expect higher classification performance for marine waters as there are mostly no other classes in the same image.

5.2. Performance Metrics

We chose to compute multiple metrics for evaluating the performance of the models in the classification tasks. We provide results for *f2-micro, f2-macro* (Implementation), *hamming-loss*, and *precision* scores (Implementation). We also calculate precision and f1 scores for individual classes.

5.3. Results

First, we calculated feature vectors using DOFA for all the images in BigEarthNet (Sentinel-I) and saved them for further use. All the following analyses use these vectors for visualizations or the downstream classification task. The distribution parameters for the Sentinel I data (wavelengths with their standard deviations) were provided by the authors of the DOFA paper and were being used for the computation of the features [20].

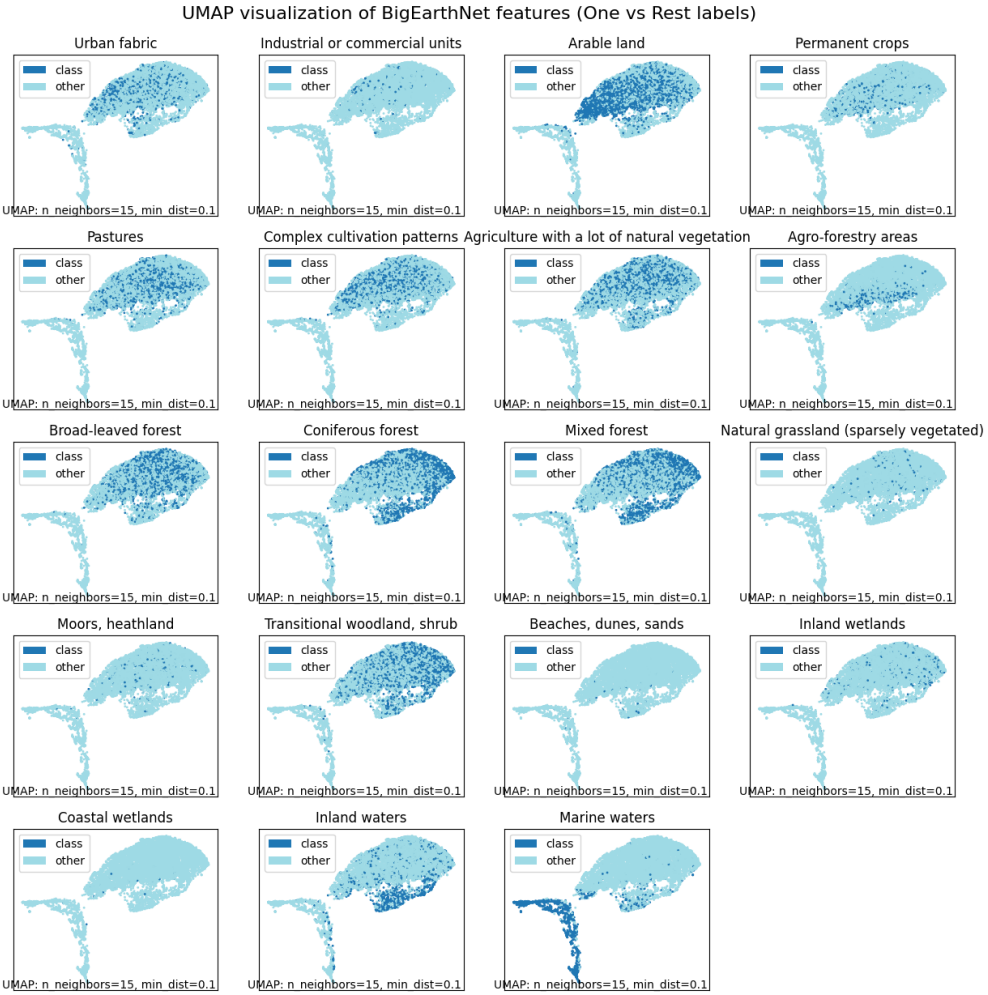

Figure 5. Visualization of the 19 classes in a UMAP transformed space (one vs. rest)

5.3.1 UMAP Feature analysis

The occurrences of different classes in a UMAP-transformed 2D space are visualized in Fig 5. Because one image has multiple labels, we chose to present the visualization using multiple charts. In this visualization, we expect different classes to be located in different data cloud regions. As we can see, this assumption holds for many of the classes. Most notably, we have a separate region for all marine water images (right-bottom chart). As we've seen in Fig. 4, this class is negatively correlated with most of the other classes, so a separation in this visualization is plausible. It appears that arable land is more on the left side of the largest region, while forests and woodlands are more on the right side.

Based on this visualization, we expect that the feature vectors of DOFA capture the semantic meaning of the different images, making it possible to train a classifier using these vectors.

5.3.2 Classification

We used the feature vectors of DOFA to train different ML algorithms for the given classification task. All the approaches use the same data split. The final results of these experiments are presented in Table 1. The random forest classifier used 20 estimators. The MLP consisted of 4 linear layers (768→384,384→192,192→100,100→19) and ReLU layers in between. The MLP was trained using the BCE loss and the Adam optimizer.

There are notable differences in the performance of the chosen approaches. MLP has the best performance over most of the metrics. However, the random forest classifier and linear probing also have similar scores in P_{micro} and P_{macro}. All classifiers have significant differences between their micro and macro averaged F^2 scores. When we compare the F^2 scores per class, we can see the cause for these values (Fig. 6): There is a

	F^2_{macro} (%)	F^2_{micro} (%)	hamming loss	P_{macro} (%)	P_{micro} (%)
Random Forest	21.4	35.8	0.123	52	**72**
Linear Probing	22.9	35.3	0.124	49	70
MLP	**34.5**	**47.8**	**0.113**	**58**	71

Table 1. Test results of different classification approaches on the 19-class multi-label classification task. Some classes contain so few examples that they are not in the test dataset and receive an F^2 score of 0.

high variance in the performance across classes, which ranges from 0% F^2 score to about 90% F^2 score. This leads to the different averaging variants resulting in different scores. We can also see that MLP manages to achieve higher scores than the linear classifier over more classes. Additionally, the low performing classes are mostly similar and correlate to the classes with low-data availability. It seems that the labels were not sufficient to learn all of the classes well.

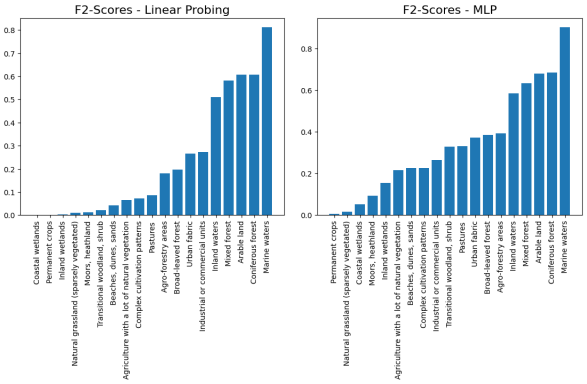

Figure 6. F^2 scores for every class (19 in total). Left side for the linear classifier, right side for the MLP classifier.

We can conclude that the features generated by the DOFA model are not easily linearly separable across all classes, with only some achieving an F^2 score of over 50%. The MLP model can separate more complex data and therefore reaches a better performance.

Random forest classifiers can separate high dimensional data, but in this case, as seen in Table 1, their scores are on the same level as the linear classifier.

In Table 2, we provide test results for the multi-label classification task with 43 classes of BigEarthNet [15]. The results are expected to be worse than on the 19-class variant, as this is a more complex task. We can see that the DOFA model isn't able to keep up with a specialized model, e.g. [14] even though this comparison has its limitations as this paper used the Sentinel-II images.

In Fig. 7, we see the confusion matrices of the best model over the 19 classes. With 19 classes, it is expected that most of the classes are quite uncommon, which results in many true negatives. Interestingly, most of the

Figure 7. Confusion matrices of the MLP classifier on the test set with 19 classes. The matrices are calculated separately for each class.

errors are false negatives, indicating that the model fails to detect certain classes in an image.

6. Conclusion

As we have seen, the DOFA model can be used to analyze the Sentinel-1 from the BigEarthNet dataset. The features from the model contain the semantic information necessary to train a classifier to predict the related class labels. However, the model struggles to provide high-quality features for classes with low availability, which leads to mediocre classification performance and doesn't keep up to the state-of-the-art.

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	F^2_{macro} (%)	F^2_{micro} (%)	**hamming loss**	P_{macro} (%)	P_{micro} (%)
Random Forest	9.46	33.73	0.056	24	**71**
Linear Probing	12.63	36.54	0.057	28	66
MLP	15.45	44.46	0.052	**38**	**71**
COMP [14]	**52.8**	**62.3**	**0.04**	/	/

Table 2. Test results of different classification approaches on the 43-class multi-label classification task. For comparison, we provide the results of a specialized model for this task [14]. This comparison is only meant as a reference as this paper uses the Sentinel-II images of BigEarthNet, which includes more spectral bands.

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