Abstract

Recognizing packaged grocery products based solely on appearance is still an open issue for modern computer vision systems due to peculiar challenges. Firstly, the number of different items to be recognized is huge (i.e., in the order of thousands) and rapidly changing over time. Moreover, there exist a significant domain shift between the images that should be recognized at test time, taken in stores by cheap cameras, and those available for training, usually just one or a few studio-quality images per product. We propose an end-to-end architecture comprising a GAN to address the domain shift at training time and a deep CNN trained on the samples generated by the GAN to learn an embedding of product images that enforces a hierarchy between product categories. At test time, we perform recognition by means of K-NN search against a database consisting of just one reference image per product. Experiments addressing recognition of products present in the training datasets as well as different ones unseen at training time show that our approach compares favourably to state-of-the-art methods on the grocery recognition task and generalize fairly well to similar ones.

1. Introduction

Automatic recognition of grocery products is receiving increasing attention as it may lead to improved shopping experience (e.g., shopping apps, interaction via augmented reality, checkout-free stores, support to visually impaired customers) as well as to a more efficient store management (e.g., by automated inventory and on-line shelf monitoring).

As pointed out by [16] in their seminal work, recognizing grocery products can be thought of as an object recognition problem featuring peculiar challenges. Firstly, the number of different items to be recognized is huge, in the order of several thousands for small to medium shops, well beyond the usual target for current state-of-the-art image classifiers. Furthermore, product recognition is better cast as an hard instance recognition rather than a classification problem, as it mandates telling apart many items looking identical but for a few details, such as the different flavours of the same cereal brand depicted in Fig. 1b-c-d. Any practical methodology should rely only on the model images available within existing commercial product databases, i.e. a single high-quality image for each side of the package either acquired in studio settings or rendered using computer graphics tools (e.g., Fig. 1c-d). Conversely, products must be recognized from images captured in the store by cheap sensors, e.g., smartphone cameras, under far less than ideal conditions (e.g., Fig. 1a). Thus, product recognition implies tackling a domain adaptation problem between the images available to build the inference engine and those deployed at test time to pursue recognition. Another peculiarity deals with the items on sale in a store as well as their appearance changing frequently overtime, which would render unfeasible to continuously re-train or fine-tune an inference engine in order to keep-up with all such changes. Differently, a practical approach should be conducive to recognition of both seen products (i.e., products whose reference images were deployed at training time) as well as unseen products (i.e., products present in the store but not used to train the inference engine).

Given these premises, we rely on a global image descriptor learned to disentangle grocery products and to pursue recognition through K-NN search within a database featuring one reference image per sought product. This approach allows for learning an image embedding based on the available training data and then perform recognition of both seen and unseen products seamlessly. For example, should a new product be put on sale in the store, our system would just require to add one image of the new product into the reference database without the need of performing a new costly retraining. K-NN search is quite amenable to product recognition from a computational standpoint alike. Indeed, compared to typical image retrieval settings, the database is very small (i.e., in the order of several thousands images rather than millions of images). Thus, a global image descriptor of about a few hundreds entries turns out viable in terms of time and memory efficiency.

We propose to learn the embedding through a deep CNN.
trained by a loss function that forces both similar looking items as well as items belonging to the same high level category to map close one to another in the descriptor space. Moreover, to tackle the domain shift issue and increase the training set size we propose to deploy an image-to-image translation GAN together with the embedding CNN and to optimize the whole architecture end-to-end. In particular, some of the training samples for the embedding network are generated by a GAN that learns unsupervisedly to transform images taken in studio settings into in-store type of images without introducing excessive modification of product appearance (Fig. 1 (b) shows an exemplar image synthesized by the GAN). These training samples force the embedding CNN to learn robustness to domain shift; moreover, the GAN can be trained to produce samples that are particularly hard to embed, thereby allowing the CNN to learn a stronger embedding function thanks to these adversarial samples. Despite the use of multiple networks, the overall architecture can be trained end-to-end effortlessly via simple gradient descent.

Thus, the main original contributions of this paper can be summarized as follows.

- The introduction of an image-to-image translation GAN trained jointly together with an embedding network in order to produce a domain-shift resilient and stronger embedding function. To the best of our knowledge, this is the first work that tries to integrate a GAN with adversarial behaviour within the training process of an embedding network.

- A novel formulation of the classic triplet ranking loss that can be used to learn a better embedding whenever in the domain of interest there exist a taxonomy between classes (e.g., ImageNet class taxonomy). Our loss helps preserving in the descriptor space the similarity information implied by the taxonomy (i.e., items belonging to the same macro class should be embedded closer than those belonging to unrelated classes).

- A novel formulation of the grocery product recognition task as an instance-level recognition problem with thousands of classes and only one sample per class. In Sec. 4 we will show how in this real-world scenario, far more challenging than the standard datasets currently used to benchmark methods aimed at learning from few shots, our proposed architecture can obtain impressive performance.

2. Related Work

Grocery Product Recognition The grocery products recognition problem was firstly investigated in the seminal paper by [16]. Together with a thoughtful analysis of the problem, the authors propose a system based on local invariant features to help visually impaired costumers shop in grocery stores. However, their experiments report performance far from conducive to real-world deployment. A number of more recent proposals are aimed at improving product recognition by leveraging on: a) stronger features followed by classification ([3]), b) the statistical correlation between nearby products on shelves ([1, 2]) c) information on the expected product disposition ([33]) or d) a hierarchical multi-stage recognition pipeline ([4]). Yet, all these recent works focus on a relatively small-scale problem, i.e., recognition of a few hundreds different items at most, whilst several thousands products are on sale in a real shop. [5] address more realistic settings and propose a quite complex multi-stage system capable of recognizing ∼ 3400 different products based on a single model image per product. The authors contribution include releasing the dataset employed in their experiments, which we will use in our evaluation. Recently [14] have shown how it is possible to improve detection and recognition performance on the same dataset relying on a probabilistic model based on local feature matching and refinement by deep network. However, even in this
work, performance appear not as satisfactory as to pave the way for practical exploitation.

Computer Vision for Retail The recognition of grocery products shares commonalities with the exact street to shop task addressed in [9, 38, 25], which consists in recognizing a real-world example of a garment item based on the catalog of an online shop. Like our solution, these works rely on matching and retrieval using deep features extracted from CNN architectures. However, they leverage on labeled paired couple of samples depicting the same item in the Street and Shop domain to learn a cross domain embedding at training time while our proposal leverages only on labeled images from one domain, thereby vastly relaxing the applicability constraint. Moreover, computer vision has been successfully applied in the retail environments for costumer profiling ([30]), automatic shelf surveying ([17]), visual market basket analysis ([23]) and automatic localization inside the store ([37]).

Embedding Learning Using CNNs to obtain rich image representations is nowadays an established approach to pursue image retrieval, both as a strong off-the-shelf baseline ([26]) and as a key component within more complex pipelines ([8], [24]) train a CNN using triplets of samples to create an embedding for face recognition and clustering. Since then, this approach has been used extensively to learn representations for a variety of different tasks, with more recent works advocating smart sampling strategies ([40]) or suitable regularizations ([41]) to ameliorate performance. Similarly to our proposal, [42] extend the idea of triplets by a novel formulation amenable to embed label structure and semantics at training time based on tuplets. Unlike [42], in this paper we propose to embed label structure within the learning process using only standard triplets; moreover our method uses only one exemplar image per class and augment the training set by a GAN trained jointly together with the embedding network.

Few Shot Learning Few shot learning has been addressed successfully by [11] through classifiers trained on top of a fixed feature representation by artificially augmenting a small training set with transformations in the feature space. Yet, in the grocery product recognition scenario the items to be recognized at test time change quite frequently, which would mandate frequent retraining of new classifiers. Besides, as product packages exhibit very low intra-class variability, the generalization ability of a classifier may not be needed. Thus, we prefer to learn a strong image embedding and rely on K-NN similarly to perform recognition. In this respect our approach shares commonalities with [35] and [29], where the authors address few shot learning by learning suitable embedding spaces and matching functions.

GANs Starting from the pioneering works of [7] and [20], GANs have received ever increasing attention in the computer vision community as they enable to synthesize realistic images with few supervision. Recently GAN frameworks have been successfully deployed to accomplish image-to-image translation, with ([13]) and without ([43, 27]) direct supervision, as well as to tackle domain shift issues by forcing a classifier to learn invariant features ([34]). We draw inspiration from these works and deploy a GAN at training time to pursue domain adaptation as well as to improve the effectiveness of the learned embedding. A related idea is proposed in [19] though, unlike [19], (a) we explicitly deploy the GAN while learning the embedding to attain domain adaptation, (b) use only one sample per class and (c) train the GAN to produce realistic though hard to embed training samples, i.e. the generator of our GAN not only plays an adversarial game against the discriminator but also against the encoder network that learns the embedding.

3. Domain invariant hierarchical embedding

An overview of our Domain invariant hierarchical embedding (DIHE) is depicted in Fig. 2. We use a deep CNN (encoder) to learn an embedding function $E : I \rightarrow D$ that maps an input image $i \in I$ to a k-dimensional descriptor $d^i \in D$ amenable to pursue recognition through K-NN similarity search. During training we exploit, if available in the training dataset, a taxonomy of classes by means of a novel loss function that forces descriptors of different items to be closer if they share some portion of the taxonomy, distant otherwise. To learn a descriptor robust to the domain shift between train and test data, we use an image-to-image translation GAN, consisting of a generator and a discriminator, which augments the training set with samples similar to those belonging to the test domain while simultaneously producing hard examples for the embedding network. The three networks can be trained jointly by standard gradient descent in order to minimize the three loss functions described in the following sections.

3.1. Hierarchical Embedding

An established approach to learn an effective image embedding consists in training a deep CNN according to the triplet ranking loss ([36]). In the original formulation, each training sample consists of three different images, referred to as anchor ($i_a$), positive ($i_p$) and negative ($i_n$). In a typical classification scenario these images would be chosen such that $i_a$ and $i_p$ depict the same class while $i_n$ belongs to a different one. Given a distance function in the descriptor
space, $d(X,Y)$, with $X,Y \in D$, and denoted as $E(i)$ the descriptor computed by the encoder network for image $i$, the loss to be minimized is defined as

$$L_{enc} = \max(0, d(E(i_a), E(i_p)) - d(E(i_a), E(i_n)) + \alpha)$$

with $\alpha$ a fixed margin to be enforced between the pair of distances.

We modify this formulation for domains that feature a hierarchical structure between classes (e.g., ImageNet classes taxonomy), so as to mimic this structure within the learned descriptor space. This is a quite common scenario for problems where a multi level classification is available. For instance, existing commercial databases of grocery products feature labels both at instance as well as at multiple category levels (e.g., for the product depicted in Fig. 1 (c) we would have three different classification labels with increasing generality: Kellog’s Special K Classic $\rightarrow$ Cereal $\rightarrow$ Food).

Our aim is to force the network to embed images nearby in the descriptor space not only based on their appearance but also on higher level semantic cues, like those shared between items belonging to the same macro-class. We argue that doing so will help producing a stronger image descriptor and may provide better generalization to products whose reference images are unseen at training time.

Assuming a taxonomy of classes encoded in a tree like structure, we propose to impose a hierarchy in $D$ by rendering $\alpha$ inversely proportional to the amount of hierarchy shared between the classes of $i_a, i_p$ and $i_n$. Considering an image sample $i$ in the training set, we denote with $c$ its fine class (foil level in the taxonomy) and with $\mathcal{H}(i)$ a set of higher level classes (all the parent nodes in the class tree excluding the common root). Using this notation and defining the minimum and maximum margin, $\alpha_{\text{min}}$ and $\alpha_{\text{max}}$ respectively, our hierarchical margin, $\alpha \in [\alpha_{\text{min}}, \alpha_{\text{max}}]$, can be computed as:

$$\alpha = \alpha_{\text{min}} + \left(1 - \frac{|\mathcal{H}(i_a) \cap \mathcal{H}(i_n)|}{|\mathcal{H}(i_a)|}\right) \cdot (\alpha_{\text{max}} - \alpha_{\text{min}})$$

where $|\cdot|$ is the cardinality operator for sets. Thus, if $i_a$ and $i_b$ share all the parent nodes $\alpha = \alpha_{\text{min}}$, whilst the margin is proportionally increased until completely disjoint fine classes will produce $\alpha = \alpha_{\text{max}}$.

### 3.2. Domain Invariance

A common trait across many computer vision tasks is that easily available labelled training data (e.g., tagged images published on-line) are usually sampled from a different distribution than the actual test images. Thus, machine learning models directly trained on such samples, such as embedding networks, will typically perform poorly at test
time due to domain shift issues. However, annotating samples from the test distribution, even if possible, is usually very expensive and time consuming. We propose to address this problem by dynamically transforming the appearance of the available labelled training images to make them look similar to samples from the unlabeled test images. This transformation is carried out by two CNNs, referred to in Fig. 2 as generator and discriminator, realizing an image-to-image translation GAN which is trained end-to-end together with the embedding network (encoder).

Given two image domains \( A, B \subset \mathcal{I} \) consisting of \( i^A \in A \) and \( i^B \in B \), the standard image-to-image GAN framework can be summarized as a generator network that tries to learns a generative function \( G : A \rightarrow B \) by playing a two player min-max game against a discriminator network \( D : \mathcal{I} \rightarrow \mathbb{R} \) that tries to classify examples either as real images from domain \( B \) or fake ones produced by \( G \). In the following we will denote with \( G(i^A) \in \mathcal{I} \) the output of the generator network given the input image \( i^A \) and with \( D(i) \in \mathbb{R} \) the output of the discriminator network for image \( i \). To generate samples similar to the images from domain \( B \) without drastically changing the appearance of the input image \( i^A \), we introduce an additional term in the generator loss function \( L_{reg} \) that, similarly to the self regularization term deployed in [27], forces \( G(i^A) \) to be visually consistent with \( i^A \). In our architecture, \( A \) is the training set while \( B \) is a small set of unlabeled images from the test data distribution.

Following the notation introduced in Sec. 3.1 during each training iteration of the whole architecture we sample one image \( i^B \in B \) to train the discriminator and two from the other domain \( i^A_p, i^A_n \in A \) to train the encoder and generator. As mentioned in Sec. 3.1 the encoder needs triplets of samples to compute its loss, so we synthesize the missing image using the generator \( i^G = G(i^A_p) \). With this architecture the triplet used to calculate \( L_{disc} \) consists of two images from domain \( A \) and one from the simulated domain \( B \), thereby mimicking the test conditions where the query images to be recognized will come from \( B \) and the reference images to perform K-NN similarity from \( A \).

The encoder is trained to minimize \( L_{disc} \) with the margin defined in Eq. 2. The discriminator tries to minimize a standard cross entropy loss:

\[
L_{disc} = \log(D(i^B)) + \log(1 - D(G(i^A_p)))
\]

while the generator minimizes a loss consisting of three terms:

\[
L_{gen} = L_{adv} + \lambda_{reg} \cdot L_{reg} + \lambda_{emb} \cdot L_{emb}
\]

\[
L_{adv} = -\log(D(G(i^A_p)))
\]

\[
L_{reg} = \phi(i^A_p, i^A_n)
\]

\[
L_{emb} = -d(E(i^A_p), E(G(i^A_p)))
\]

with \( \phi(x, y) \), \( x, y \in \mathcal{I} \) a similarity measure between the appearance of image \( x \) and \( y \), either at pixel level (e.g., mean absolute difference...) or at image level (e.g., SAD,ZNCC...), and \( \lambda_{reg}, \lambda_{emb} \) two hyper parameters that weigh the different terms of the loss function. We refer the reader to Sec. 4.1 for the actual \( d(x, y), \lambda_{reg}, \lambda_{emb} \) and \( \phi(x, y) \) used in the experiments. The contribution of the three terms can be summarized as follows. \( L_{adv} \) is the standard adversarial loss for the generator network that forces the synthesized images to be indistinguishable from those sampled from domain \( B \); \( L_{reg} \) is aimed at synthesizing images that preserve the overall structure of the input ones (avoiding thereby the mode collapse issue often occurring in GAN generators); \( L_{emb} \) forces an additional adversarial behaviour against the encoder, so as to create hard to embed samples.

At training time, given a minibatch of \( M \) different triplets of samples \( (i^A_p, i^A_n, i^B) \), the three networks are trained jointly to minimize their average loss on the \( M \) samples.

4. Experimental Results

4.1. Implementation Details

**Datasets** To evaluate the effectiveness of DIHE in recognizing grocery products we rely on two products datasets comprising thousands of items: the publicly available Grocery Products dataset [5] and a standard commercial database, referred to here as Product8600. Both datasets include more than 8500 grocery products, each described by exactly one studio-quality (reference) image of the frontal
face of the package, and feature a multi level class hierarchy in the categorization of products. As already discussed, at test time we pursue recognition from a different set of images (query). To create this set, for Grocery Products we automatically cropped individual items from the available shelf images according to the annotation released in [33], thereby obtaining a total of 938 query images. As for Product8600, we cropped and annotated individual items from shelf videos that we acquired in a grocery store by a tablet camera, for a total number of 273 query images. As the shelf images available in Grocery Products concern only items belonging to the Food macro class, which accounts for 3288 products, we consider also this smaller subset of products, which will be referred to as Grocery_Food, whilst Grocery_Full will denote all the products of the Grocery Product dataset. We depict in Fig. 3 the taxonomy of macro categories that compose the Grocery_Food dataset which we are going to use as training set, each categories features several fine grained classes (one for product) not depicted in figure. As for the samples from domain B needed to train the discriminator and generator of our architecture (see Sec. 3.2), we have used 547 additional images cropped from the shelf images available in Grocery Products, picked as to have no overlap with the previously mentioned 938 query images used at test time. We wish to point out how our formulation requires images from domain B only for the discriminator of the GAN system. Therefore, few samples without any kind of annotation are sufficient to learn the appearance of products on the shelf. Moreover we can use images from domain B that depict any kind of product, even items not in A.

Network architectures. For the implementation of DIHE we have used tensorflow\[1\] as our deep learning framework. For all our test we used as generator U-Net (\[21\]) and as discriminator PatchGAN (\[13\]), the latter producing a dense grid of predictions for each input image. For the encoder we tested different available CNN model with or without pretrained weight on the ImageNet-1000 classification task. For the initialization of the encoder network on the fine tuning tests we have used the weights publicly available in the tensorflow/models repository. The three network that compose DIHE can easily fit in a single GPU, so training our system, once implemented, in a deep learning framework is straightforward.

Descriptor Computation. We will show how for the grocery product recognition scenario, the best performance can be achieved using as embedding the maximum activation of convolution features (MAC [32]). We extract these descriptors from different layers, concatenate them and finally perform L2-normalization to get a final representation laying on the unit hyper-sphere. For all our tests, we used as distance function \(d(X, Y) = 1 - X \cdot Y\) with \(X, Y \in D\) (i.e., one minus the cosine similarity between the two descriptors).

Training Details. As for \(\phi\) in \(L_{reg}\), we tried the pixel-wise \(L1\) or \(L2\) norms, the Structured Similarity Index (SSIM) (\[39\]) and the Zero Mean Normalized Cross Correlation (ZNCC) and found out the last to work best in all our tests, in the following \(\phi(x, y) = ZNCC(x, y)\). The weights of each network are trained to minimize their specific loss functions as introduced in Sec. 3. We use Adam (\[15\]) as optimizer with different learning rates for the different tests. Concerning data preprocessing, we use as input colour images with fixed size of \(256 \times 256\) and intensities rescaled between \([-1, 1]\). To obtain the input dimension the original images are rescaled to the target resolution preserving the aspect ratio and filling the extra pixels with 0s. The only additional data augmentation is a preliminary random crop with size at least 80% of the original image to attain the input of the generator network.

Evaluation Protocol. To test our embedding network we encode all the reference images of the considered dataset to create a reference database, then compute the same encoding for the query images. For each query vector we perform similarity search against all the reference vectors and retain the K most similar database entries; if the reference image for the product depicted in the query does belong to this set of nearest neighbours we consider recognition to be successful. As a measure of effectiveness of the embedding, we report the accuracy (number of successful recognitions over number of queries) for different K values.

Based on these premises, we train once and for all our architecture using only the reference images belonging to Grocery_Food, (i.e., one reference image for each of 3288 different products organized in a multi level hierarchy of products categories). We then use the trained embedding model to address three different test scenarios:

(a) Grocery_Food: we recognize the 938 query images from Grocery Products based on the 3288 reference images from Grocery_Food. Thus, all the reference images were deployed at training time.

(b) Grocery_Full: we recognize the 938 query images from Grocery Products based on the 8403 reference images from Grocery_Full. Thus, only 40% of the reference images were deployed at training time.

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[1] https://www.tensorflow.org/
[2] https://github.com/tensorflow/models/tree/master/research/slim
(c) Product8600: we recognize the 273 query images cropped from our videos based on the 8597 reference images from Product8600. Thus, none of the reference images was deployed at training time.

Among the three, (b) is the most likely to happen in practical settings as product appearance changes frequently overtime and it is infeasible to constantly retrain the embedding network, although perhaps a portion of the reference images dealing with the items actually on sale in the store had been used at training time.

At test time the encoder network is used as a stand alone global image descriptor. Our implementation is quite efficient and can easily encode, on GPU, more than 200 image per second taking into account also the time needed to load the images from disk and rescale them to the 256 × 256 input size. Finally, given that usually our reference database only provides a single image per product and the descriptor dimension is relatively low (between 256 and 1024 floats across different tests), we perform the K-NN similarity search extensively without any kind of approximation. The biggest descriptor database considered in our tests is the one obtained from Product8600 using a 1024 float dimensional embedding vector (i.e., the reference database is a matrix of float with 8600 row and 1024 column). Even on this kind of database given a query descriptor the whole similarity search can be solved in a tenth of second using brute force search, nevertheless the search could be speeded up using KD-Tree or approximate search technique.

4.2. Ablation Study

To understand the impact on performance of the different novel components proposed in our architecture, we carry out a model ablation study using as encoder PatchGAN ([13]) with MAC features ([32]) extracted from the last convolutional layer before the output. We use this randomly initialized small network to better highlight the gains provided by the different kind of proposed losses. We will show how to obtain the best performance we rely on a larger pre-initialized network. We train this architecture on the reference images of Grocery_Food according to six different training losses and report the accuracy dealing with the three test scenarios presented in Sec. 4 in Tab. 1. In particular, with reference to the first column, triplet denotes training by triplet loss with fixed margin (α = 0.3 obtained by cross validation); hierarchy denotes training by our triplet loss with variable margin introduced in Sec. 3.1 (α_{min} = 0.1, α_{max} = 0.5); entries with +GAN denote deploying the image translation GAN to generate the anchor image \( \ell_a \) (Eq. 3), \( \lambda_{reg} = 1, \lambda_{emb} = 0 \); finally, entries with +GAN+adv concerns introducing also the adversarial term in the loss of the GAN generator (Eq. 4) \( \lambda_{reg} = 1, \lambda_{emb} = 0.1 \). For all the models that do not use GANs, we rely on standard data augmentation techniques (e.g., crop, gaussian blur, color transformation . . .) to obtain the anchor image given the positive one. In all the tests the networks are randomly initialized and trained for the same number of steps and identical learning rates.

The results reported in Tab. 1 show how each individual novel component proposed in our DIHE architecture provides a significant performance improvement with respect to the standard triplet ranking loss. Indeed, by comparing rows (2),(4) and (6) to (1),(3) and (5), respectively, it can be observed that modifying the fixed margin of the standard triplet loss into our proposed hierarchically adaptive margin can improve accuracy with all models and in all scenarios, with a much larger gain in (c) (i.e., completely unseen reference images). This proves that embedding a hierarchy into the descriptor space is an effective strategy to help learning an embedding amenable to generalize to unseen data. The main improvements are clearly achieved by methods featuring a GAN network to pursue domain adaptation by generating training samples similar to the images coming from the test domain. Indeed, comparison of (3) and (4) to (1) and (2), respectively, highlights how performance nearly double across all models and scenarios, testifying that the domain shift between test and train data and the lack of multiple training samples are indeed the key issues in this task that the proposed image-to-image translation GAN can help to address very effectively. Finally, comparing (5) and (6) to (3) and (4), respectively, vouches that training the generator to produce anchor images not only realistic but also hard to embed turns out always beneficial to performance. Indeed, the adversarial game played by the generator and encoder may be thought of as an on-line and adaptive hard-mining capable of dynamically synthesize hard to embed samples that help training a more robust embedding. Performance of our overall DIHE architecture are reported in row (6) and show a dramatic improvement with respect to the standard triplet loss, row (1).

4.3. Product Recognition

Model and Descriptor Selection To ameliorate product recognition performance we can rely on larger networks pre-trained on the ImageNet classification benchmark. To chose the best CNN model as our encoder network we downloaded the public available weights of different models trained on ImageNet-1000 classification and test them as general purpose off-the-shelf feature extractors on our datasets without any kind of fine tuning. We considered three different popular CNN models (VGG16 [28], resnet[50/101/152] [12], and inception_v4 [31]) and compute three kind of different descriptors from activations extracted at various layers:

- **Direct**: directly use the vectorized activation of a given layer. The dimension of the descriptor is the number of elements in the feature maps for that layer.
Table 1: Ablation study for DIHE. Recognition accuracy for 1-NN and 5-NN similarity search in the three considered scenarios. Best results highlighted in bold.

|                      | (a) Grocery_Food | (b) Grocery_Full | (c) Product8600 |
|----------------------|------------------|------------------|------------------|
| Training loss        | K=1              | K=5              | K=1              | K=5              | K=1              | K=5              |
| (1) triplet          | 0.301            | 0.430            | 0.277            | 0.390            | 0.351            | 0.490            |
| (2) hierarchy        | 0.325            | 0.491            | 0.302            | 0.433            | 0.355            | 0.553            |
| (3) triplet+GAN      | 0.454            | 0.626            | 0.418            | 0.586            | 0.512            | 0.706            |
| (4) hierarchy+GAN    | 0.479            | 0.660            | 0.455            | 0.621            | 0.538            | 0.699            |
| (5) triplet+GAN+adv  | 0.470            | 0.648            | 0.431            | 0.595            | 0.548            | 0.717            |
| (6) hierarchy+GAN+adv (DIHE) | **0.481** | **0.688** | **0.463** | **0.642** | **0.553** | **0.732** |

- AVG: perform average pooling on the feature map with a kernel with width and height equals those of the map. Therefore, we use as descriptor the average activation of each convolutional filter for a given layer. The dimension of the descriptor is the number of convolutional filters in the selected layer.

- MAC [32]: perform max pooling on the feature map with a kernel with width and height equals those of the map. Therefore, we use as descriptor the maximum activation of each convolutional filter for a given layer. The dimension of the descriptor is the number of convolutional filters in the selected layer.

We applied the three different descriptors above at different layers of the three networks and report in Tab. 2 the 1-NN accuracy using the test protocol described in Sec. 4.2. For all our tests the descriptors were L2 normalized to unit norm and the similarity search is performed using cosine similarity. In Tab. 2 we report only some of the best performing layers for each network and additional tests where the descriptors are obtained by concatenation of representations extracted at different depths in the CNN (e.g., conv4_3+conv5_3 is the concatenation of representations extracted at layers conv4_3 and conv5_3) with L2 normalization performed after concatenation.

Looking at the results in Tab. 2 we can observe how, in our settings, newer and more powerful CNN, like inception_v4 or resnet_152, fail to achieve the same instance-level distinctiveness of VGG_16. We conjecture that deeper architectures, trained on Imagenet, tend to create more abstract representations that may not provide out-of-the-box features distinctive enough to tell apart many items looking almost identical as required by our problem. Some evidence to support this conjecture may be found in Tab. 2 due to deeper layers providing typically inferior performance when compared to shallower ones (e.g., VGG_16: conv5_3 vs conv4_3, resnet_50,resnet_101,resnet_152: Block4 vs Block3) Concerning the type of descriptor to use, from Tab. 2 it seems quite clear that MAC descriptor is the best choice for grocery recognition with respect to AVG or direct activations of fully connected layers.

Given these results, we selected for our fine tuning tests the VGG_16 network with MAC descriptor computed on the concatenation of conv4_3 and conv5_3 layers, and train the overall architecture according to our losses. As the encoder is already pre-trained, we perform 5000 iterations of pre-training for the generator and discriminator [eq. 4]

\[ \lambda_{reg} = 1, \lambda_{emb} = 0 \] before training jointly the whole DIHE architecture. The chosen hyper-parameters obtained by cross validation for the training process are as follows. Learning rates $10^{-5}, 10^{-5}$ and $10^{-6}$ for generator, discriminator and encoder, respectively; $\lambda_{emb} = 0.1$, $\lambda_{reg} = 1$, $\alpha_{min} = 0.05$ and $\alpha_{max} = 0.5$.

Before comparing our proposal to other embedding losses, it is interesting to verify whether the improvements provided by the different components (Sec. 4.2) are valid even when relying on the VGG-16 network pretrained on Imagenet. Purposely, we carry out the same ablation study as in Tab. 1 and report the results in Tab. 3. Indeed, the ranking of performances among the different training modalities turns out coherent, although, as expected, the margins are smaller due to the higher performance provided by the baseline.

**Comparison with other embedding losses** We compare our architecture to the already mentioned concatenation of MAC descriptors without fine tuning (MAC) and to our implementation of different embedding learning methods: [36] fine tuning using the classic triplet ranking loss (Triplet); [10] fine tuning using Siamese networks and the contrastive loss (Siamese); Matching networks [35] without the full context embedding which does not scale to thousands of classes (MatchNet); [42] triplet loss to embed label structure (Structured); and [41] triplet loss regularized by a spread out term (Spread). Similarly to DIHE, all methods are trained on the reference images of Grocery_Food starting from the very same VGG16 pre-trained on ImageNet-1000 and using the same concatenation of MAC descriptors.
| Network   | Layer        | Descriptor | Grocery_Food | Grocery_Full | Product8600 |
|-----------|--------------|------------|--------------|--------------|-------------|
| **VGG_16** | conv4_3      | MAC        | 0.789        | 0.785        | 0.717       |
|           | AVG          |            | 0.515        | 0.510        | 0.538       |
|           | conv5_3      | MAC        | 0.724        | 0.720        | 0.611       |
|           | AVG          |            | 0.406        | 0.398        | 0.395       |
|           | conv4_3+conv5_3 | MAC   | **0.792**    | **0.787**    | **0.725**   |
|           | AVG          |            | 0.501        | 0.493        | 0.523       |
|           | fc6          | Direct     | 0.560        | 0.549        | 0.549       |
|           | fc7          | Direct     | 0.444        | 0.433        | 0.432       |
| **inception_v4** | Mixed_7a      | MAC        | 0.610        | 0.603        | 0.509       |
|           | AVG          |            | 0.673        | 0.670        | 0.560       |
|           | Mixed_7b     | MAC        | 0.652        | 0.641        | 0.512       |
|           | AVG          |            | 0.675        | 0.668        | 0.5091      |
|           | Mixed_7a+Mixed_7b | MAC | 0.655        | 0.646        | 0.534       |
|           | AVG          |            | 0.690        | 0.685        | 0.542       |
| **resnet_50** | Block3       | MAC        | 0.731        | 0.729        | 0.703       |
|           | AVG          |            | 0.441        | 0.433        | 0.432       |
|           | Block4       | MAC        | 0.654        | 0.646        | 0.509       |
|           | AVG          |            | 0.571        | 0.558        | 0.465       |
|           | Block3+Block4 | MAC  | 0.723        | 0.720        | 0.644       |
|           | AVG          |            | 0.547        | 0.538        | 0.545       |
| **resnet_101** | Block3       | MAC        | 0.737        | 0.735        | 0.695       |
|           | AVG          |            | 0.389        | 0.388        | 0.432       |
|           | Block4       | MAC        | 0.636        | 0.662        | 0.490       |
|           | AVG          |            | 0.570        | 0.556        | 0.417       |
|           | Block3+Block4 | MAC  | 0.714        | 0.708        | 0.626       |
|           | AVG          |            | 0.535        | 0.524        | 0.520       |
| **resnet_152** | Block3       | MAC        | 0.708        | 0.703        | 0.655       |
|           | AVG          |            | 0.345        | 0.337        | 0.446       |
|           | Block4       | MAC        | 0.571        | 0.561        | 0.435       |
|           | AVG          |            | 0.571        | 0.561        | 0.435       |
|           | Block3+Block4 | MAC  | 0.678        | 0.671        | 0.542       |
|           | AVG          |            | 0.506        | 0.500        | 0.504       |

Table 2: 1-NN accuracy for different general purpose descriptors obtained from layers of network pre-trained on the ImageNet-1000 classification dataset without any kind of additional fine-tuning. Best results are highlighted in bold.

| Network   | Layer        | Descriptor | Grocery_Food | Grocery_Full | Product8600 |
|-----------|--------------|------------|--------------|--------------|-------------|
| **VGG_16** | conv4_3      | MAC        | 0.789        | 0.785        | 0.717       |
|           | AVG          |            | 0.515        | 0.510        | 0.538       |
|           | conv5_3      | MAC        | 0.724        | 0.720        | 0.611       |
|           | AVG          |            | 0.406        | 0.398        | 0.395       |
|           | conv4_3+conv5_3 | MAC   | **0.792**    | **0.787**    | **0.725**   |
|           | AVG          |            | 0.501        | 0.493        | 0.523       |
|           | fc6          | Direct     | 0.560        | 0.549        | 0.549       |
|           | fc7          | Direct     | 0.444        | 0.433        | 0.432       |

Table 3: Ablation study for DIHE on a VGG-16 network pretrained on ImageNet-1000. Recognition accuracy for 1-NN and 5-NN similarity search in the three considered scenarios. Best results highlighted in bold.
as embedding function.

We use the same test scenarios presented in Sec. 4.2 and report the result in Tab. 4. As already shown in our model study, MAC activations have strong absolute performance without any need of fine tuning with accuracy at K=1 ranging from 0.72 in the worst case to 0.79 in the best. Starting from such a strong baseline the standard Triplet loss is able to only slightly increase performance in scenario (a) and (c) while being slightly penalized in (b), which testifies how in the cross domain and low shot regime is quite hard to properly fine tune an embedding network. The additional regularization term introduced by Spread does not seems to help with a slightly decrease in performance across all scenario compared with the standard Triplet. Structured is the first method to consistently improve performance across all scenario, vouching the importance of deploying label structure in the embedding space for this type of recognition task. Siamese based on a simple contrastive loss is able to obtain performance comparable to Structured on scenario (a) and (b) while performing slightly worse on the generalization to dataset (c). MatchNet is definitely the best competing method for embedding learning in a few shot regime as testified by the good improvement obtained with respect to the initial MAC descriptors. Nevertheless, DIHE thanks to the combined use of GAN and hierarchical information is still able to improve the performance, obtaining recognition accuracies for K=1 consistently over 82% across all test. It is worth pointing out that the largest improvement, with respect to the initial MAC results, is obtained on the completely unseen products of the Product8600, which vouchers for mixing GAN-based domain adaptation and hierarchical embedding to learn an embedding that can generalize very well to unseen items.

In Fig. 4 we report the accuracy of the methods while increasing K. In Fig. 4 (a-b) almost all methods converge to more than 95% accuracy for K > 30. However, DIHE can provide substantially better results for lower values of K. In Fig. 4(c) DIHE still outperforms the competitors with performance almost equal to those achieved by Matching Networks but showing higher margin against the competitor trained with variant of triplet ranking loss.

4.4. Beyond product recognition

To investigate on the generality of our proposal as an improvement over established embedding learning methods, we perform additional tests on the Office31 benchmark dataset for domain adaptation (22). This dataset consists of 4652 images dealing with 31 classes of office objects acquired in three different domains, namely Amazon, concerning ideal images downloaded from the web, Webcam, consisting of real images acquired by cheap cameras, and DSLR, featuring real images acquired by an high quality camera. Akin to the setup of Grocery Recognition experiments, we use Amazon as the reference set, thus deploying these images to train the encoder, while images from Webcam and DSLR are used both as training samples for the GAN discriminator in DIHE and as two separate query sets for the tests. This scenario is compliant to the full protocol setting described by (6): train on the entire labeled source and unlabeled target data and test on annotated target samples. Unfortunately, as the Office31 dataset does not provide a taxonomy of classes, in these additional experiments DIHE can not leverage on the hierarchical loss to improve the learned representation. However, unlike the Grocery Recognition scenario, all methods can be trained here by more than one sample per class.

Based on the above described experimental setup, we train different encoders starting, once again, from a VGG16 network pre-trained on the ImageNet-1000 dataset. We report the accuracy for 1-NN and 5-NN similarity search in Tab. 3. To asses the performance of DIHE we compare it once again against the methods considered in Sec. 4.3, with the exception of Structured due to Office31 lacking a class taxonomy. The first two rows of Tab. 3 show that, differently from the the Grocery Recognition setup, between activations extracted from the pretrained VGG16 network, FC6 outperforms MAC descriptors (computed as in Sec. 4.3). Coherently with the findings of Tab. 2, we believe this difference to be due to the office task concerning the recognition of category of objects rather than instances. Accordingly, to obtain the encoder network for these tests we substitute the original FC6 layer with a smaller fully connected layer consisting of 512 neurons with randomly initialized weights and then perform fine tuning on the Amazon images.

In this different experimental settings wherein more training samples per class are available, both Siamese, Spread Out and Matchnet are outperformed by the plain Triplet ranking loss of (30), which turns out the best performing established method achieving a 1-NN accuracy of 59% and 62% for test datasets Webcam and DSLR, respectively. Yet, thanks to the introduction of the Generator in the training loop, DIHE can yield a significant performance improvement reaching a 1-NN accuracy of 62% (+3%) and 66% (+4%) for Webcam and DSLR, respectively, with best or comparable 5-NN accuracy when compared with competing methods using descriptors with the same dimension. Moreover, our proposal can outperform the descriptor extracted by FC6 that is twice larger on 3 experiments out of 4, obtaining comparable performance on the fourth.

Although performance on Office31 turns out well below the state-of-the-art attainable by image recognition methods based on classifiers, amenable to handle a fixed and possible small number of classes, we argue that the experiments reported in this Section further highlight the advantages provided by our proposed DIHE architecture with respect to
Table 4: Recognition accuracy for 1-NN and 5-NN similarity search in the three considered scenarios. Best results highlighted in bold, differences between DIHE and best performing competitor reported in the last line.

| Descriptor      | (a) Grocery_Food | (b) Grocery_Full | (c) Product8600 |
|-----------------|------------------|------------------|-----------------|
|                 | K=1              | K=5              | K=1            | K=5            | K=1 | K=5            |
| MAC             | 0.792            | 0.917            | 0.787          | 0.9093         | 0.725 | 0.908          |
| Triplet [36]    | 0.799            | 0.922            | 0.775          | 0.894          | 0.765 | 0.915          |
| Spread [41]     | 0.784            | 0.916            | 0.764          | 0.893          | 0.758 | 0.923          |
| Structured [42] | 0.809            | 0.931            | 0.804          | 0.926          | 0.750 | 0.912          |
| Siamese [10]    | 0.810            | 0.931            | 0.805          | 0.928          | 0.733 | 0.926          |
| MatchNet [35]   | 0.834            | 0.939            | 0.810          | 0.929          | 0.820 | 0.948          |
| DIHE            | **0.853**        | **0.948**        | **0.842**      | **0.942**      | **0.827** | **0.959**    |
|                 | +0.02            | +0.01            | +0.03          | +0.02          | +0.007 | +0.01          |

Figure 4: Accuracy with increasing K in the three scenarios.

Table 5: Recognition accuracy for 1-NN and 5-NN similarity search on two subset of the Office31 using as reference images the Amazon subset. Best resulted highlighted in bold, differences between DIHE and best performing competitor reported in the last line.

| Descriptor      | (a) Webcam | (b) DSLR |
|-----------------|------------|----------|
|                 | K=1 | K=5 | K=1 | K=5 |
| MAC             | 0.382 | 0.640 | 0.393 | 0.660 |
| Triplet [36]    | 0.596 | 0.675 | 0.628 | 0.710 |
| Spread [41]     | 0.591 | 0.660 | 0.590 | 0.670 |
| Siamese [10]    | 0.469 | 0.547 | 0.576 | 0.630 |
| MatchNet [35]   | 0.522 | 0.579 | 0.566 | 0.618 |
| DIHE            | **0.628** | **0.691** | **0.662** | **0.742** |
|                 | +0.03 | -0.007 | +0.03 | +0.03 |

4.5. Qualitative Results

Fig. 5 and Fig. 6 report some successful recognitions obtained by K-NN similarity search based on DIHE. The upper portion of Fig. 5 dealing with the Grocery_Food scenario, shows query images for products quite hard to recognize due to both the reference database featuring several items looking remarkably similar as well as nuisances like shadows and partial occlusions (first query) or slightly deformed products (third query). The lower portion of Fig. 5 concerns the Product8600 scenario: as clearly highlighted by the third and second query, despite differences between items belonging to the same brand and category (e.g., the pasta boxes in the last row) being often subtle, DIHE can recognize products correctly. In Fig. 6, we report some results dealing with the Office-31 dataset which vouch how DIHE can correctly retrieve images depicting objects belonging to the same category as the query. In Fig. 7, we highlight some failure cases. In the first row DIHE wrongly recognizes a stapler as a bookshelf, whilst in the second a ring binder is mistaken as a trash bin. In the third row DIHE seems to recognize the macro class and brand of the query product though missing the correct instance level label (i.e., the correct NN, highlighted in green, is retrieved as the 3-NN). A similar issue pertains the fourth query image: all the first 5-NNs belong to the Tea macro class, but the correct item is not ranked among them.

Finally, in Fig. 8 we show some training images gener-
ated by our GAN framework to pursue domain invariance (Sec. 3.2). It is worth observing how the training samples created by our GAN seem to preserve both the overall structure and details of the input images, which is very important when addressing instance level recognition between many similarly looking items, while modifying significantly the brightness and colors and injecting some blur, thereby realizing a domain translation between the input and output images.

5. Conclusion

The experimental results demonstrate how our proposed hierarchical modification to the triplet ranking loss is effective in learning embedding functions that generalize better to unseen data. Moreover, the integration of a GAN at training time, so as to obtain the whole DIHE architecture, turns out a very effective approach in scenarios where only few/one samples per class are available at training time. Indeed, DIHE allows for learning a representation not only robust to domain shift but also better all around due to the Generator network effectively producing potentially infinite hard training samples. DIHE was designed to solve the task of Grocery Product recognition, in which it can deliver remarkably good performance. Nonetheless, experiments in different scenarios suggest that our architecture may be effectively deployed in settings that features challenges such as few training samples per class, different domains between train and test data and a taxonomy among classes to be recognized. The results of the ablation study of Sec. 4.2 show clearly how the main improvement in performance is provided by the original introduction of a GAN network trained end-to-end together with the embedding network in order to augment the training set. In the future we would like to further investigate on this novel concept through different combination of embedding losses and GAN architectures. For example, a possible variant of DIHE may concern a GAN that would operate at the feature embedding level rather than at image level, thereby hallucinating embedding vectors from the domain $\mathcal{B}$ given those from domain $\mathcal{A}$, with these vectors amenable to compute any kind of embedding loss.

Finally, in this paper we have proposed an architecture to recognize a product item extracted from a shelf image, though we did not address how to actually detect the individual product items within such an image. Recent works like [13] have shown how a region proposal CNN can be successfully trained to extract bounding boxes surrounding grocery products from an image featuring the whole shelf. Thus, [13] and DIHE may be combined effortlessly in a complete pipeline that given a single shelf image and one reference image for each product can detect and recognize the displayed items.

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Figure 6: Qualitative results for K-NN similarity search by DIHE on the Office31 dataset. Upper portion: Amazon→DSLR scenario, lower portion: Amazon→Webcam.

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Figure 7: Some wrong recognitions yielded by DIHE on the different datasets.

Figure 8: Images generated by the GAN trained jointly with the embedding network in DIHE for the Office31-Amazon→Webcam (left) and Grocery_Food (right) scenarios. Columns labeled as Original depict images provided as input to the Generator while those labeled as Generated show the corresponding outputs.
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