Abstract—Retail Product Image Classification is an important Computer Vision and Machine Learning problem for building real world systems like self-checkout stores and automated retail execution evaluation. In this work, we present various tricks to increase accuracy of Deep Learning models on different types of retail product image classification datasets. These tricks enable us to increase the accuracy of fine tuned convnets for retail product image classification by a large margin. As the most prominent trick, we introduce a new neural network layer called Local-Concepts-Accumulation (LCA) layer which gives consistent gains across multiple datasets. Two other tricks we find to increase accuracy on retail product identification are using an instagrampretrained Convnet and using Maximum Entropy as an auxiliary loss for classification.

I. INTRODUCTION

Retail product image classification is the problem of deciphering a retail product from its image. This recognition of products from images is needed in a lot of Computer Vision applications in the real world like self-checkout shops, retail execution measurement and shopper behavior observation. Convnets (Convolutional Neural Networks) have been shown to give the best performance for many image classification datasets. Transfer Learning is a method to train a Deep Learning model on a small dataset by finetuning a model pretrained on a larger dataset. This practice is especially more prevalent with convnets which respond very well to this method. This work aims to figure out the best method to finetune deep convnets for different types of retail product classification datasets.

Classifying and identifying retail product images is a very important component of systems where one needs to automate or analyze retail practices. It can help in making a self-checkout store by providing an interface to recognize products for automatic billing, help automate retail supply chain by automating product logging, can help automatically evaluate retail-execution evaluation when combined with a retail product object detector or help analyze consumer behavior in retail stores in combination with a video analysis system.

Deep Learning algorithms have gathered interest recently due to their performance and applicability in the real world[1]. Convolutional Neural Networks (convnets), a type of Deep Learning algorithm has beaten the state of the art results for various Computer Vision tasks like image classification[2], object detection[3] and image matching[4]. In scenarios like identifying retail products, where often only a relatively small number of training images per class are available (sometimes just a few product packshots[5]), finetuning[6] of pre-trained weights is generally the preferred mode to train the convnet in use. Few shot classification techniques[7] are often used in combination with finetuning when only a few images per class are present. Our aim in this work is to come up with a set of tricks which give high accuracy across different retail product classification datasets when finetuning convnets.

Our contributions in this work are: 1. We introduce Local-Concepts-Accumulation layer, which gets consistent accuracy gains across datasets, 2. We show that Maximum-Entropy loss[7] can be used as an auxiliary loss in combination with Local-Concepts-Accumulation to increase the classification accuracy even more, 3. We show that a model of the exact same size pretrained on Instagram and then imagenet[8] gives better accuracy than a model pretrained just on Imagenet.

II. RELATED WORK

Deep Learning[1] systems have been making inroads into many cognitive automation tasks. In case of retail, there is a lot of scope to make existing workflows efficient using Deep Learning. Localizing and classifying retail objects on retail shelves has been studied in the past. Traditional Image Processing features SIFT[9] and Harris corners[10] have been used for detecting and identifying retail products. [11] proposes using SIFT features[9] with a hybrid approach combining SVM with HMM/CRF for context aware product detection and identification. [12] introduces Grozi-120 dataset and uses SIFT[9] for product identification as baseline. [13] introduces CAPG-GP dataset and uses a combination of Deep Learning[6] and SIFT[9]/BRISK[14] for product recognition. [15] compares visual bag of words and deep learning on grozi dataset for both detection on shelves and classification. [16] tries out dense pixel based matching, bag of words and genetic algorithms for exemplar based product matching. [17] uses Object Detection algorithms for one-shot product detection and identification. [18] uses BRISK features[14] and graphs to verify planograms. [19] uses GAN based training of convnet embeddings for fine-grained product image classification.

With the recent introduction of generic retail object detectors from retail shelves like [3] and [20], the problem of retail object detection from shelves and retail object identification can be separately solved. In this work, we show methods to improve finetuning[6] of convnets for image classification of retail objects.
Convnets have been shown to work very well for image classification problems[21]. It has also been shown that models pretrained on imagenet dataset can be finetuned on other smaller datasets[6] for classification to achieve better accuracy. ResNext architecture[2] is one of the best-performing deep learning architectures for image classification. ResNext architecture has residual connections with bottleneck dimensions between layers and also has multiple paths within each layer. Resnext architecture when trained on a larger Instagram dataset and finetuned on imagenet, gives state of the art accuracy on imagenet[8]. It is shown, such a network trained on Instagram, also called ResNext-WSL[22] is very robust to image noise and perturbations[23].

Traditionally, image matching techniques using descriptors like BRISK[14] and SIFT[9] have also been used to identify retail products. Superpoint[4] is a convnet based keypoint detection and keypoint matching algorithms that has recently shown better results than SIFT. Superpoint is trained on a synthetic dataset and then finetuned on Image augmentations to become invariant to various distortions. We use Superpoint as a baseline in all benchmark tasks.

Fine-grained classification is a classification task where classes of images are visually similar to each other. Maximum Entropy Loss[7] has been used to make classification in such scenario more effective. We use Maximum Entropy loss as we find the ‘lack of diversity of features’ hypothesis true in all retail product image classification, just like it is true in fine-grained classification.

III. METHODOLOGY

We present three tricks which make convnets more effective at recognizing retail product images. We try this on three different datasets which represent different scenarios which arise while working with retail images in real world. First trick we present is that a convnet[8] pretrained on Instagram[22] images and then finetuned later on imagenet works better for retail product classification than a convnet pretrained on imagenet[21] alone. The second trick is the new type of neural network layer called Local-Concepts-Accumulation layer which can be added to any convnet architecture as its penultimate layer while training or finetuning. ResNext architecture as it is proposed that focusing on local concepts makes it more effective. We try this on three different datasets which represent different scenarios which arise while working with retail images in real world. First trick we present is that a convnet[8] pretrained on Instagram[22] images and then finetuned later on imagenet works better for retail product classification than a convnet pretrained on imagenet[21] alone. The second trick is the new type of neural network layer called Local-Concepts-Accumulation layer which can be added to any convnet architecture as its penultimate layer while training or finetuning. We show that adding LCA layer while finetuning convnets for retail product image classification gives sizable gains in accuracy across all datasets we present our results on. The hypothesis to use this layer is that there are multiple large or small ‘local concepts’ in retail product images which when individually recognized and then aggregated can be used to classify the product.

A. Finetuning an Instagram pretrained model

ResNext[2] architecture has shown state of the art classification accuracy on classification tasks in the past. We thus chose it as our baseline architecture to finetune for retail product image classification. It has been shown that a ResNext model pretrained on Instagram[22] images using hashtags as training labels before finetuning it on imagenet[21] gives state of the art results on imagenet classification[8]. This convnet, also known as ResNext-WSL model, has been shown to have more robustness on common image corruptions and perturbations[23].

We show that using a pretrained ResNext-WSL with the same number of parameters gives better accuracy than a pretrained ResNext on imagenet (we refer this ResNext model pretrained just on imagenet as ResNext-INet henceforth to contrast it with ResNext-WSL). We use the “resnext-101_32X8” pretrained models (both ResNext-INet and ResNext-WSL) available from pytorch[24] repositories for finetuning. Both the networks require exactly the same resources for finetuning as they have the same number of parameters and we finetune them with exactly the same hyperparameters. We find that finetuning ResNext-WSL gets gains in accuracy for all datasets we work on. It seems that ResNext-WSL gets better gain in accuracy on datasets where test images have more noise and distortions.

B. Local-Concepts-Accumulation layer

We introduce a new layer called Local-Concepts-Accumulation (LCA layer) which can be added to any convnet architecture as its penultimate layer while training or finetuning. We show that adding LCA layer while finetuning convnets for retail product image classification gives sizable gains in accuracy across all datasets we present our results on. The hypothesis to use this layer is that there are multiple large or small ‘local concepts’ in retail product images which when individually recognized and then aggregated can be used to classify the product.

Fig. 1. Figure showing hypothesized local concepts on a retail product. The top left image is of the retail object itself. The top right image is of various possible local concepts marked on image. The bottom row has images showing all the possible local concepts shown individually.

The hypothesis further is that when a convnet is trained to classify pooled features from the last layer, it focuses more on the global look and feel of the retail product rather than on the local features. When we use different local concepts as features and aggregate their contribution with equal importance, the classifier focuses on both individual local concepts and global look and feel. It is proposed that focusing on local concepts would give a boost in classification accuracy.
Fig. 2. This figure explains the implementation of Local Context Aggregation Layer (LCA Layer). The feature maps of pretrained convnet (size #FMs × Height × Width) are averaged pooled by kernels of different sizes and the pooled feature maps are then scrambled into vectors of #FMs size. These vectors are then passed through a Fully Connected layer to give rise to different “Local Concepts” vectors. The Local Concepts Vectors are then aggregated by averaging into the final vector for the image.

Implementation-wise, in a LCA layer, we build features for all possible local concepts in an image and aggregate them by averaging. These aggregated features are then fed to the classifier layer. This LCA layer can be used during finetuning any pretrained convnet when placed between pretrained layers and classification layer. The implementation of LCA layer can be visualized in Figure 2.

For a resnext-101_32X8 architecture, LCAlayer is placed between the pretrained convolutional layers of the ResNext architecture and the last FC classification layer. All possible rectangle and square kernels larger than 1X1 are used to average pool the feature map from pretrained network and get corresponding pooled feature maps. The number of feature maps remains the same before and after each individual average pool operation. Now all the pooled feature maps after average pool operations are scrambled into vectors, each of dimension of number of feature maps in ResNext pretrained output. Each of these vectors is passed through a fully connected layer followed by Relu nonlinearity. Figure 3 shows arrangement of layers when finetuning the ResNext architecture along with LSA layer. The Neural Network is trained with Stochastic Gradient Descent with Momentum.

C. Maximum Entropy loss as an auxiliary loss

Maximum Entropy loss has been previously used for fine grained visual classification[7]. We show that using Maximum Entropy loss as an auxiliary loss in retail product image classification loss betters the accuracy of the convnet. This might be due to the fact that the diversity of features in retail dataset is not as high as real world objects and diversity of features within classes is not that high too. Authors of [7] propose that Maximum Entropy loss can be useful in such circumstances. The structure of the loss function can be found in Figure 4.

$$\theta^* = \arg\min_\theta \hat{E}_{x\sim D} \left[\text{KL}(y(x) \| p(y|x;\theta)) - \gamma H[p(y|x;\theta)]\right]$$

Fig. 4. The Maximum Entropy Loss Function

The description of Entropy (quantity H in equation of Maximum Entropy Loss) over a conditional distribution can be found in Figure 5.

$$H[p(\cdot|x;\theta)] = -\sum_{i=1}^{m} p(y_i|x;\theta) \log(p(y_i|x;\theta))$$

Fig. 5. Entropy over a conditional probability distribution

A weighted average between Negative Likelihood loss and Maximum Entropy loss is used as the final loss term for finetuning the neural networks.

IV. DATASETS

In this section, we describe the various datasets used for experiments. We also explain how these datasets are analogues to real-world problem statements.

A. Baselines

We choose two baselines to show the effectiveness of our method. The first baseline is a simple finetuning[6] of a ResNext[2] model pretrained on imagenet only (referred to as ResNext-INet). These baselines give an idea about how much the tricks we implement one on the top of other, aid classification accuracy. The other baseline is keypoint detection and matching using convnet based Superpoint algorithm[4]. This is because keypoint matching based identification is common in many retail product image classification systems. Also, Superpoint is one of the leading methods for keypoint detection and feature matching. This gives us a good upper bound on what retail product identification systems using image matching could achieve.
B. Grozi-120 dataset

Grozi-120 dataset[12] (available at link) is a dataset having images of 120 retail products. Some products in the dataset are for example: Cheerios, Cheez-it, Snickers etc. We take in-vitro images of retail products as training data and in-situ images were taken as testing data. Typically, the number of in-vitro images is 4-6 per class. These in-vitro training images are packshots[5] taken from the internet and thus many augmentation techniques were applied on the images before finetuning the convnet for classification. Figure 6 shows a few pairs of in-vitro / in-situ images. In real world use cases, such type of classification problem often comes up where one gets only pack shots for training and the classifier trained has to work on images from shops/retail outlets.

C. CAPG-GP dataset

CAPG-GP[13] (available at link) dataset has 102 retail products for fine grained one-shot classification. All products have just one training image. However, the training images are not pack shots but a small number of good quality images of actual products. In real world, an analogous classification problem often comes up where a few high quality images are available to train the classifier and the classifier trained is supposed to work on product images from shops/retail outlets. Image augmentations to incorporate different types of distortions into train set are introduced while the convnet is finetuned. Figure 7 shows a few pairs of train and test set images.

D. DM4VM dataset

DM4VM dataset (available at link)[25] is a dataset of 10 retail products with 60-70 images in training set per product and approximately 30 images per product in the test set. Both the training and test images appear to be real world images taken from shelves. Figure 8 shows pairs of train and test set images. A real world usecase analogous to this dataset is when data is collected from real world shelves and is annotated in a considerable number to train a classifier which again has to work in similar domain as training data.

V. Results

We now present the results of our experiments on various datasets to show the accuracy gains the proposed tricks achieve. As mentioned earlier, our baselines are classification by image matching (keypoint detection + keypoint matching) using Superpoint[4] and finetuning Resnext[2] pretrained on Imagenet (ResNext-INet). We then show accuracy of our tricks added one on the top of the other. We show results when finetuning ResNext-WSL[8] on the retail product classification datasets. When ResNext-WSL is trained along with addition of the LCA layer, the model thus trained is referred to as ResNext-WSL-LCAlayer. When Resnext-WSL with LCA layer is finetuned with a mutlitask learning loss combining Negative Likelihood loss and Maximum-Entropy loss, the model is called ResNext-WSL-LCAlayer-ME. The performance numbers are test set classification accuracy in %age.

| Method / Dataset | Grozi-120 | CAPG-GP | DM4VM |
|------------------|-----------|---------|-------|
| Image Matching with Superpoint | 44.8% | 84.7% | 96.16% |
| ResNext-INet | 58.66% | 83.9% | 99.3% |
| ResNext-WSL | 60.4% | 84.1% | 100% |
| ResNext-WSL-LCAlayer | 70.8% | 90.4% | 100% |
| ResNext-WSL-LCAlayer-ME | 72.3% | 92.2% | 100% |

When we analyze the results, we can come to a set of conclusions. ResNext-WSL gets better accuracy than ResNext-
INet for all datasets, but its gets a relatively higher accuracy boost in Grozi-120, where the test images have a lot of distortions and noise. We can attribute this to the robustness pretraining it on Instagram gives to the model. Adding an LCA layer gives a sizable accuracy boost in all the datasets showing it is a good methodology for any type of retail product image classification problem. Max-Entropy loss gives an accuracy boost across all datasets too, reinforcing that the hypothesis of the inventors that, it is a good add-on loss wherever low-diversity of features is seen in the training data.

VI. CONCLUSIONS

We propose multiple tricks that better the accuracy of retail product image classification in multiple datasets. The technique of using an Instagram and later imagenet pretrained convnet instead of imagenet pretrained convnet only is very simple to apply and gives performance boost without adding any parameters. A new layer for neural networks is proposed called LCA layer which, when added during finetuning, gives consistent accuracy gain across all datasets. We also show that using maximum-entropy loss as an auxiliary loss makes the classifier work better.

ACKNOWLEDGMENT

I thank my colleagues Srikrishna, Sonaal and Harshita for their help in calculating baselines using keypoint matching as well as in the implementation of maximum entropy loss.

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