Abstract—In this work, we perform a wide variety of experiments with different Deep Learning architectures in small data conditions. We show that model complexity is a critical factor when only a few samples per class are available. Differently from the literature, we improve the state of the art using low complexity models. We show that standard convolutional neural networks with relatively few parameters are effective in this scenario. In many of our experiments, low complexity models outperform state-of-the-art architectures. Moreover, we propose a novel network that uses an unsupervised loss to regularize its training. Such architecture either improves the results either performs comparably well to low capacity networks. Surprisingly, experiments show that the dynamic data augmentation pipeline is not beneficial in this particular domain. Statically augmenting the dataset might be a promising research direction while dropout maintains its role as a good regularizer.

I. INTRODUCTION

Machine Learning (ML) popularity has rapidly increased thanks to the success of Deep Learning (DL) [2]. In particular, convolutional neural network (CNN) architectures, have achieved considerable success in a wide range of computer vision tasks including object classification [3], object detection [4] and semantic segmentation [5], just to cite a few. The two main ingredients that have favored the rise of this type of algorithms are i) networks with deeper structure and ii) the use of large annotated datasets. The latter requirement can not always be fulfilled for several reasons. Obtaining and labeling data is needed to achieve strong results but this process might be extremely expensive or not possible at all. For instance, in the medical field, high-quality annotations by radiology experts are often costly and not manageable at large scales [6]. Several sub-domains of ML are trying to mitigate the necessity of training data, tackling the problem from different perspectives. Transfer Learning aims at learning representations from one domain and transfer the learned features to a closely related target domain [7], [8]. Similarly, Few-Shot Learning uses a base set of labelled pairs to generalize from a scarce support set of target classes [9]. Both approaches have gained much attention in the community but still require a large source of annotated data. Furthermore, the target domain must be related to the source domain. Another research direction is trying to reduce the demand for annotations. This field is referred to as Self-Supervised Learning. Usually, a large pool of images is used to teach how to solve a pretext task to a CNN [10]. This task does not require human annotations and is conceived to teach general visual features that can be transferred to the downstream task. In this manner, costly human annotations are not needed but there is still the problem of collecting many images. In general, we would like to have systems that are able to recognize objects from just a few exemplars.

In this work, we present a detailed empirical study of DL models in the small data regime. Similarly to what has been done in [11] and [12], we consider a small data problem, a task for which not more than a thousand samples per class are available at training time. Due to the great difficulty, only a handful of works has studied such a problem. Indeed, it is very hard to train function approximators when the availability of multi-dimensional points to interpolate is scarce. Any ML model is highly prone to overfit the training dataset, especially if its complexity is too high to handle the current task. CNNs have proved to be extraordinarily resistant to overfitting, although the number of trainable parameters is usually much greater than the number of data points [13]. In this paper, we show that model complexity is a critical factor in small data domains and that small nets are better than big ones. A large number of works have proposed techniques to increase the generalization capabilities of DL networks. For instance, data augmentation is commonly used to fight the data scarcity problem and to increase generalization [14]. We do not use data augmentation in our comparative analysis to strictly benchmark the architectures’ resistance to overfit. However, in other experiments, we show that the standard dynamic augmentation pipeline does not improve performance when only a few samples are available and that static augmentation might be preferred. The augmentation type should also be carefully designed since its success, is highly correlated to the image type. Moreover, dropout is an extremely popular technique that regularizes neural networks [15] by randomly dropping units to prevent co-adaptation and to favor generalization through ensembles. In this paper, we show that dropout is a good regularizer even when data is scarce but not when the number of samples per class is extremely low (e.g. 10). Finally, it has been experimentally proven and studied that multi-tasking in DL serves as a regularizer and improves generalization [16]. In order to exploit the unsupervised regularizer induced by the reconstruction loss, we implement the supervised autoencoder (SAE) model presented in [1] and we expand it with multiple
Fig. 1: A schematic view of the three classifiers augmented with unsupervised losses. From left to right, the SAE [1], SASD-flip and SASD-rot.

decoders that have to perform self-supervised tasks. Such predictions slightly improve the results of low complexity CNNs in two out of three datasets. We will refer to this model as supervised autoencoder with self-supervised decoders (SASD).

In summary, the contributions of this paper are the following: 1) we perform a large set of experiments with different quantities of training data and DL architectures over three popular computer vision benchmarks; 2) we show that for small data problems, low capacity CNNs are much more effective than high capacity ones and that our proposed new model (SASD architecture) and standard low complexity CNNs, improve the state of the art of DL with small data; 3) we demonstrate that the impact of standard regularization techniques like data augmentation is not always beneficial and that might be modified for small data regimes. On the other hand, we show that dropout results to be a good regularizer even in these settings.

II. RELATED WORK

As previously said, very few works have tried to tackle the problem of training DL architectures with a small number of samples due to the high susceptibility of these ML models to overfit. We use this section to provide a summary of the main achievements in these scenarios and to describe the direct competitors of our architectures. Although they did not test deep neural networks, we cite the work of Fernández-Delgado et al. [17] that found out the superiority of random forests in small data problems using the UCI Repository. A subsequent study in [18] generalized the results of [17] adding DL feed-forward architectures. Results were comparable to the ones of random forest classifiers. However, both works did not test CNNs since inputs were not images. On the contrary, Hu et al. [19] proposed a method to improve the facial recognition ability when data is scarce by generating new images combining parts of the face coming from parent images. In the medical field, He [20] used a generative adversarial network (GAN) to generate lung CT scans and therefore improve the reliability and the generalization of learning. Despite the great interest in this technique, we do not implement data generation in this work since we consider it as a different sub-problem of small data domains. We leave such approaches as future works. On the other hand, the studies [11] and [12] are closely related to our work. In [11], the authors proposed the use of the cosine loss to prevent overfitting on datasets with only a handful of samples per class. They obtained the best results on fine-grained datasets that have between 66 and 555 classes and between 20 and 80 samples per class. We will show that in our experiments the cosine loss does not provide better performance than the cross-entropy and for this reason, more studies on the matter are necessary. Arora et al. [12] suggests the use of neural tangent kernels in low data tasks. They showed the superiority of neural tangent kernel (NTK) architectures on the UCI testbed. They also performed experiments with convolutional neural tangent kernel (CNTK) networks on small CIFAR-10 and on a Few-Shot Learning problem. We provide empirical evidence that our approaches perform better than CNTK on the small CIFAR-10 task.

III. SMALL DATA CLASSIFICATION PROBLEM

In this section, we first outline the definition of the small data classification problem, followed by describing the DL architectures studied in our experiments. Finally, we describe the datasets used in this work.

A. Problem definition

As a standard ML problem, given a training distribution of images $X$ and a label distribution $Y$, our objective is to learn a classifier $f_\theta$, parametrized by a set of variables $\theta$, such that for any image $x \sim X$ with corresponding label $y \sim Y$, $y = f_\theta(x)$. Let us suppose that our distribution is made of $K$ different classes and that our training dataset sampled from $X$ and $Y$, is composed of $N$ images per class.

Differently from the standard computer vision datasets, we choose to keep $N$ extremely low. Despite the notion of low is highly subjective, we follow the protocol used in [12] for the definition of the small CIFAR-10 task. Therefore, $N$ is doubled each time starting from $N_{min} = 10$ up to $N_{max} = 1280$. In this manner, it is easy to benchmark models capabilities when
TABLE I: This table shows the number of kernels for each convolutional layer (i.e. c1, c2 ...) coming from the blocks of our models. We set the depths of the ResNet-20 blocks to 32, 64 and 128. The number of trainable parameters is expressed in millions (M).

FIG. 2: Experiments regarding the influence of model complexity. Results, over the test sets, are in terms of accuracy, averaged over 20 runs.

FIG. 3: Experiments regarding the use of regularization techniques. Results, over the test sets, are obtained with the CNN-mc and are in terms of accuracy, averaged over 20 runs.

few samples are available. In general, there is no specific limit that regards the number of classes K.

B. Models

We introduce a novel architecture, SASD, and test three known models. More precisely, SAE, CNN and ResNet-20. A schematic view of the SAE and SASDs is shown in Fig. 1.

SAE. SAEs were introduced in [1] and were proposed to improve generalization by the inclusion of an unsupervised regularizer. More precisely, the reconstruction error of the autoencoder. A SAE differs from a standard autoencoder because an additional output is added at the bottleneck layer. This output is trained to minimize the supervised error deriving from the classification problem. Let us define an encoder function that maps an input image x to a compressed representation z through a parametric function \( f_\phi(\cdot) \) as \( z = f_\phi(x) \). Furthermore, we define a decoder function \( f_\gamma(\cdot) \) that is trained to reconstruct x taking the output of the encoder as input \( \hat{x} = f_\gamma(z) \). The SAE is trained to minimize the loss function:

\[
\frac{1}{t} \sum_{i=1}^{t} \lambda_0 L_c(y_i, f_\theta(z_i)) + \lambda_1 L_r(x_i, \hat{x}_i)
\]

assuming that \( L_c \) represents the classification loss, \( L_r \) the reconstruction loss and that \( \lambda_0 \) and \( \lambda_1 \) are two hyperparameters that weight the two contributions.

SASD. Taking inspiration from the Self-Supervised Learning literature, we generalize the idea of SAE by incorporating multiple reconstruction losses to the unsupervised problem. Such additions are expected to help generalization since a)
multi-tasking improves generalization in DL and b) features that are learned by Self-Supervised Learning models have been shown to transfer well on different datasets. If we define a transformation \( T \) that is applied to the input image \( x \), we obtain another image that might be used as a target. Ideally, autoencoders are reconstructing the input \( x = T(x) = I \circ x \) assuming that \( I \) is the identity mapping and \( \circ \) the element-wise product. We generalize to the case of multiple transformations and we refer to each transformation as \( T_j \). We instantiate a decoder function \( f_{\gamma_j}(\cdot) \) that is trained to reconstruct the transformed image \( T_j(x) \). The overall loss might be written as:

\[
\frac{1}{t} \sum_{i=1}^{t} \left[ \lambda_0 L_c(y_i, f_0(z_i)) + \sum_j \lambda_j L_c(T_j(x_i), f_{\gamma_j}(z_i)) \right]
\]

(2)
in this case with \( j \) decoders and hyperparameters \( \lambda \). We experiment with two types of SASD. We will refer to the first one as SASD-flip since the model learns to reconstruct the input image and its horizontally-flipped version. On the other hand, the second SASD is called SASD-rot that has to reconstruct the image rotated counter-clockwise by 90°, 180° and 270°. In summary, SASD-flip is made of two decoders while SASD-rot of three.

**CNN.** We test a standard CNN architecture made of convolutional and max-pooling layers as feature extractors. The entire network minimizes the standard classification loss:

\[
\frac{1}{t} \sum_{i=1}^{t} L_c(y_i, f_0(x_i))
\]

(3)

More details about the structure will follow.

**ResNet-20.** Residual networks were introduced in [21] to improve the training of very deep neural networks. The basic learning block of such networks is the residual block. ResNets are made of different blocks of stacked layers (convolutions with non-linear activation functions and batch normalization). Shortcut connections join the input of each block to the output. This addition helps gradients to flow backward and ease the training of the overall network. ResNet-20 minimizes the same loss described in Eq. [3].

**Models structure.** We almost keep the same structure for our custom models. The CNN, SAE and SASD process the input image through three convolutional layers (padding enabled). The first two are followed by a max-pooling layer with stride and pool size equal to 2. The autoencoders have filters with size equal to 5, 5 and 3 while the CNN 4, 4 and 3. For the classification problem, the bottleneck of SAE and SASD is processed by another max-pooling and convolutional layer before being flattened and fed to a Dense layer. For the reconstruction problem, the bottleneck is upsampled twice and processed by three convolutional layers with filter sizes equal to 3.

**Models complexity.** In order to perform analyses regarding the influence of model complexity on the final performance, we vary the number of parameters. The complexity is directly controlled by the number of filters in convolutional layers. For this reason, we fix the lowest model complexity for the CNN by setting an initial number of filters. For each layer, we simply double their number in order to increase complexity. We define a low, medium and high complexity CNN that we will call CNN-nc, CNN-mc, CNN-hc. We set the complexity of SAE, SASD-flip and SASD-rot close to the one of CNN-nc. A detailed description can be found in Tab. [1]. We also report the complexity in terms of parameters of ResNet-20. We do not describe the full structure of ResNet-20 that can be found in [21]. For what concerns the kernel depths of the ResNet-20 blocks, we set them to 32, 64 and 128 throughout all experiments.

**Training setup.** All trained models have been optimized with Adam optimizer with default parameters [22]. The number of epochs was fixed to 50 and the batch size to 32. For each run, the maximum value of the accuracy scored on the testing set was considered. We mainly use the categorical cross-entropy as classification loss (\( L_c \)). When specified, we perform some comparisons with the cosine loss proposed in [11]. For what concerns reconstruction losses of the autoencoders \( L_r \), we use MSE. The \( \lambda \) hyperparameters in SAE and SASDs have not been tuned. We left them all set to 0.5.

**C. Regularization techniques.**

We adopt two popular regularization techniques for some of our experiments.

**Dropout.** We use dropout in the dense layer of the convolutional architectures. We set the dropping-rate probability to 0.7. We will show that such a high rate is necessary to prevent overfitting except for rare cases.

**Data augmentation.** Increasing the dataset variability by performing data augmentation techniques has been shown to improve generalization of DL models even when a great quantity of data is available [13]. Usually, the input is augmented at each epoch, constituting a non-static dataset. We refer to this augmentation as standard augmentation. In our case, input images are randomly horizontally-flipped, rotated (20°), zoomed (0.2 percentage), width-shifted and height-shifted (0.1 percentage) and brighten/darken. We used a very simple augmentation policy since in this work, we were not interested in benchmarking more sophisticated augmentation techniques. On the other hand, we also tried a static augmentation approach. In this case, we set the training set dimension to \( N_{\text{max}} \cdot K \cdot 8 = 102400 \). In this way, each image was augmented off-line \( \frac{N_{\text{max}} \cdot K}{N} \) times following the previously mentioned augmentation policy. For instance, when \( N = N_{\text{max}} \), each image is augmented 8 times while when \( N = N_{\text{min}} \) 1024 times. In preliminary analyses, we have noticed that the performance for each dimension flattens after a certain number of augmentations since the generated images are mainly copies of the original ones. We have chosen this policy to keep the dimension of the dataset fixed. However, it would have been possible to try different strategies.
We perform our experiments on three popular computer vision datasets, namely FMNIST (Fashion-MNIST) [23], SVHN [24] and CIFAR-10 [25]. We have chosen datasets made of ten classes and relatively low dimensionality since the restrictions imposed on the number of samples per class makes the problem already very challenging. Since all three original datasets contain several samples per class (many more than our defined \(N_{\text{max}}\)), we build, for each dimension, a sampled version of the original dataset. Here, we set the notation to generalize the protocol followed in [12]. We will refer to any downsampling version of any dataset as \(s\text{DatasetName} = n_{\text{samples}}\). For instance, sCIFAR-10-20 indicates the downsampling version of CIFAR-10 with twenty samples per class sampled from the training set. Differently than \(s\text{FMNIST}\) and \(s\text{SVHN}\), the addition of training samples is not changed. Following this protocol, any dataset can be transformed into a small data problem. Results must be averaged over different runs to ensure consistency. As done in [12], the number of runs is set to 20.

IV. RESULTS

A. Influence of models complexity on performance

We analyze the impact of model complexity in our small data classification problems. For this reason, we have chosen to test the three standard CNNs with increasing complexity (CNN-lc, CNN-mc, and CNN-hc) and the ResNet-20 architecture that has the highest number of trainable parameters (check Tab. 1 for more details). The results of this analysis are shown in Fig. 2. The standard CNNs consistently outperform the ResNet-20 in the sCIFAR10 problem when \(N\) is smaller than 640 samples. Only when \(N = N_{\text{max}}\) we spot a better accuracy from ResNet. The difference is roughly 10% for sCIFAR10-10 slowly decreasing until approximately zero for sCIFAR10-640. It is interesting to note that also the CNN-lc keeps a consistent gap despite it has roughly two orders of magnitudes fewer parameters than ResNet-20. Similar behavior can be noted in sFMNIST and sSVHN with the only difference that the biggest model increases its performance more rapidly. This is probably due to the intrinsic difficulty of the classification problem. When the training and testing distributions are more similar (e.g. sFMNIST or sSVHN), the addition of training samples helps the classifier at a faster rate. In both sFMNIST and sSVHN, ResNet starts to have a comparable accuracy when the number of samples per class is at least 160. Before that level, it is clear that ResNet-20 is overfitting the training dataset. The gap reaches a net difference in terms of average accuracy of around 30% for sSVHN-40 and of 20% for sFMNIST-10. For what concerns the comparison between the CNNs, we note that results are comparable although there is a significant difference in terms of model complexity (i.e. CNN-hc has more than one order of magnitude further parameters than CNN-lc). The CNN-hc scores a higher average accuracy over all three datasets and the difference decreases as the training set increases.

B. Influence of regularization techniques on performance

Here, we study how two popular regularization techniques such as dropout and data augmentation influence performance when a few samples are available. Fig. 3 shows the results of the CNN-mc on the three datasets. We start by describing the difference in performance between the CNN-mc with and without dropout. For all three cases, dropout regularizes the dense layer of the classifier. The improvement is more pronounced in sCIFAR10 (up to 5% net difference) but still consistent on the other datasets when at least 40 samples per class are available. The only case in which dropout degrades the performance is sSVHN-10. We can note that the gain in mean accuracy is smaller when a few samples are available and raises as that sample size increases. This behavior can be consistently noted for all three datasets.

The previously cited networks (with and without dropout) have only been trained with \(N\) samples per class. Although the comparison is not totally fair a priori, we want to test the influence of the previously described data augmentation policies (maintaining dropout). In these two cases, the CNN-mc is not trained with \(N \cdot K\) images. Specifically, the network processes \(N_{\text{max}} \cdot K \cdot 8\) images in the case of static augmentation and \(N \cdot K\) images randomly augmented at each epoch in the case of standard augmentation. Surprisingly, the standard augmentation pipeline does not improve performance in these low data settings. For sCIFAR10 the maximum performance lost is relatively small (max 1 – 2%) while for both sFMNIST and sSVHN is severe. In sFMNIST, the performance is constantly degraded by 5 – 7% mean accuracy while in sSVHN we can reach a net negative difference of more than 20%. We may partially link this fact to the low variability in terms of poses and perspectives of testing images in sFMNIST and the high quantity of noise caused by neighbor digits in sSVHN. However, this reasoning does not apply to sCIFAR10, where rotations, flips, etc., should improve generalization. Moreover, the static augmentation approach, despite applying the same transformations, is consistently better than standard augmentation. Therefore, it is probable that dynamically augmenting the dataset in these settings would require many more epochs to converge or that the training dynamics are unstable due to this continuous change. On the other hand, the static augmentation policy constantly improves the mean accuracy of sCIFAR10. The improvement is of roughly 5% percentage in terms of mean accuracy. The static augmentation approach for sFMNIST performs comparably to the network without augmentation, until \(N = 160\). Then, the accuracy flattens. A similar trend can be noted for sSVHN with the difference that the variance increases when more samples are available. As we previously said, we believe that the standard augmentation operations that we used in this work do not perfectly match the semantics of the images from SVHN and FMNIST. Therefore, to improve performance in such cases, more complex data generation techniques (e.g. GANs) should be preferred. However, considering the results obtained with sCIFAR-10, it seems that statically augmenting the dataset...
TABLE II: Comparison of the approaches considering all downsampled datasets. Models are trained without any kind of data augmentation. Results, over the test sets, are given in terms of accuracy averaged over 20 runs. We do not report standard deviations to improve table readability. The values are roughly constant among models for each training set dimension and decrease as the dataset size increases. For each dataset, the best value per column is reported in bold. Moreover, the first groups contain the state of the art, the central groups refer to known models that we have tested for the first time in small data conditions and the last groups to the new models that we have introduced. *We train the CNN-mc with the cosine loss proposed in [11] following our setup.

could be a good approach to improve performance in small data scenarios with natural images. Moreover, we have shown that combining the use of dropout and static augmentation can determine an improvement of performance in the range of roughly 5 – 10%. The maximum improvement is obtained in sCIFAR10-320 with a net difference of 9.8%, rising the mean accuracy from 49.8% to 59.6%.

C. Models comparison without data augmentation

In Tab. II we show the results of our models and we compare them with the approaches proposed in [11] and [12] (when applicable). In this analysis, we only report the results of the CNN-mc. We do not show in the table the mean accuracy of the CNN-hc and CNN-lc to maintain a fair comparison with the SAE and SASDs in terms of parameters.

Starting from sCIFAR10, it is clear that all the models proposed in our work (including ResNet-20) consistently outperform the CNTK proposed in [12]. We note that the SASD-flip and SASD-rot are alternately the best performing models when N ≤ 80. We believe that this is due to the unsupervised regularization induced by the reconstruction losses. When the sample size increases, the CNN-mc surpasses the other networks, except for sCIFAR10-1280 where ResNet-20 scores the highest accuracy. We have also trained the same CNN-mc architecture with the cosine loss proposed in [11]. However, we note that this loss either degrades the performance of the CNN-mc either makes it comparable (see also Fig. 4). Indeed, the model trained with the cross-entropy loss is more performant in almost all cases. The four exceptions are the tests of sFMNIST with N from 20 to 160, where results are still comparable. We presume that the dataset and the model setup greatly influence the final performance. The experiments in [11] where run with high capacity neural nets (i.e. ResNet-34, ResNet-50) on mainly fine-grained datasets with a greater number of classes. We hypothesize that the cross-entropy loss coupled with high capacity models and small samples per class is highly prone to overfit the training set. This is also what we figured out from the analysis of models complexity previously exposed (see Sec. IV-A). On the other hand, the training error of the cosine loss goes to zero more smoothly resulting in a smaller risk of overfitting when few samples are available.
This is an interesting line of research that should be deepened further. For what concerns the sFMNIST problem, we note that the influence of the reconstruction error makes the accuracy of SASDs either comparable, either greater than the one scored by the CNN-mc.

Finally, we analyze the results obtained for the sSVHN task. Here, we can notice that, in the very scarce data regime (i.e. $10 \leq N \leq 80$), the accuracy of the CNN-mc is the highest. While the ResNet-20 becomes the best model for $N \geq 160$, when more samples are available. This is probably related to the low dissimilarity between training and testing distributions, as we explained in Sec. IV-A. In these settings, the unsupervised regularizer does not seem to be effective. We suppose that this is caused by the dataset type. Indeed, it is possible that learning to reconstruct the rotated version of a number can confuse the classifier (i.e. 6s and 9s are easily misunderstood). Moreover, the reconstruction task includes the noisy digits that are often present in the proximity of the central digit that should be classified. It is probable that this kind of semantic noise degrades the features learned by the encoder network and consequently the performance of the classifier in this specific dataset.

V. CONCLUSIONS

In this work, we have tackled the problem of image classification with few samples per class. Although the results are still very far from the successes of high capacity models with tons of data, we encourage the community to contribute in order to improve Deep Learning capabilities in small data regimes. We have run several experiments and trained different flavors of DL architectures on three popular computer vision datasets. In the experiments regarding the influence of model complexity on performance, we have shown that networks with a low number of trainable parameters are less prone to overfitting and generalize better with small data. Therefore, architectures that will be proposed in the future, should not only be compared with state-of-the-art models (e.g. ResNet-34), but also with simpler networks. Through a wide analysis, we have shown that our proposed models improve the state of the art. Furthermore, we run a preliminary analysis to test the benefits of using popular regularization techniques such as data augmentation and dropout in small data settings. We figured out that the first one is not always beneficial and is highly dependent on the application modality. We have also shown that static augmentation with transformations that preserve image semantics improve performance and should be considered as a future research direction. For what concerns dropout, we have shown that it consistently improve results and should also be used in low data settings. For future works, we would like to test our models on different datasets and implement more sophisticated data augmentation techniques. Moreover, we would like to test generative models and follow the approach proposed in [29] to artificially augment the number of training samples.

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