Art Style Classification

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TASK AND MOTIVATION

Task :

We aim to classify a given artwork as belonging to a particular artistic style. Style of an artwork refers to its distinctive visual elements, techniques and methods (ex: Baroque, Cubism etc).

Motivation:

- Large amount of artistic data is being digitised and made available in recent years. Automatic categorization, indexing and retrieval of this data is therefore important.
- Automatic art style categorization poses an interesting challenge since each style is a complex interplay between distinctive visual elements, techniques and methods. Each style(or art movement) has contributions by different painters who have their own unique styles and each painter may have contributed to different movements.

Related Work:

- Comparison between using various hand crafted features and CNN for style classification(AlexNet)[1].
- Style classification using Self Organized Maps [2].
- SVM classification of features(correlation maps) extracted from CNN [3].
- Style classification using ResNet [4].
- Multitask learning for style, artist and art type classification [5].

GOALS

- Implement a deep learning model to classify art styles and evaluate the model and compare it to previous methods [1][3][4]. We will create a dataset of 30 most popular(with the largest number of images) image styles from the WikiArts dataset for this task. We will also evaluate our model on a test dataset from a different distribution(Painting-91 dataset).
- The WikiArts dataset has class imbalance in the ratio of 1:100 images if used as a whole, we aim to experiment with class imbalance rectification techniques and report our findings. For this task we may need to use the whole WikiArts dataset or sample appropriately(this is not well defined at the moment).

Mid-term milestones:

- Create datasets and preprocess as necessary.
- Set up baselines - the models in [1][3][4] to obtain their performance on our dataset.
- Experiment with the state of the art models mentioned in the next slide and choose the model that works best for our application.

METHODS & ARCHITECTURES

Considering the extreme class imbalance of the data corresponding to different artistic styles we are planning to experiment with 2 different learning paradigms.

Approach 1: (Supervised Learning):

- To achieve better classification accuracies compared to the baselines defined we propose to exploit 'Aggregated Residual Transformations for DNN [ResNeXt 101]' architecture pre-trained on ImageNet which would be used as a CNN based feature extractor.
- Architecture Reference: https://arxiv.org/pdf/1611.05431.pdf
- Library/Tools:
  - https://pytorch.org/hub/pytorch_vision_resnext/
  - https://github.com/facebookresearch/ResNeXt

Approach 2: (Self-Supervised Learning):

- To efficiently tackle this class imbalance issue, we intend to employ an Ensemble of Auto-Encoding Transformations [EnAET] which train on labelled & self-supervised representations of data by decoding both spatial and non-spatial transformations, this approach is slightly different than the vanilla semi-supervised method.
- Architecture Reference: https://arxiv.org/pdf/1911.09265.pdf
- Library/Tools: https://github.com/maple-research-lab/EnAET

Related work:

ResNeXt 101: 1st runner-up (Image Classification) in ImageNet Large Scale Visual Recognition Challenge 2016 [9].
EnAET: State-of-the-art accuracy in Semi-Supervised Image Classification on CIFAR-10 [8].

DATA CURATION

Datasets:

- WikiArt [6] : We will create a dataset of 30 most popular(with the largest number of images) image styles from WikiArt dataset. Divide the dataset into train, validation and test images. Our model will be evaluated on this test set.

- Painting-91 [7] : To evaluate our model on test data from a different distribution (Painting-91 dataset), we will use images not used in the first dataset that belong to the same 30 classes as above.

- Since we want to additionally remediate the effects of class imbalance in WikiArt dataset, we may need to use the whole WikiArt dataset or sample appropriately (this is not well defined at the moment).

- Custom Dataset (For Approach 2): Self-Supervised embedded representations of the labelled images are generated using spatial and non-spatial transformations. This is applied on the WikiArt dataset.

Data-Preprocessing (For Approach 2):

Following transformations are applied on the training images: Projective, Affine, Similarity, Euclidean, Color, Contrast, Brightness & Sharpen

EVALUATION

Metric:

- Per-class accuracy for each style type and mean of it as the final accuracy score for the complete dataset.
- Precision, Recall scores for each class and overall mean for complete dataset.

We evaluate the per-class accuracy of our model against the baseline scores achieved for top-30 styles as well as the whole dataset of imbalanced classes.

As our dataset is highly imbalanced and correlated, we use precision, recall along with per class accuracy and mean of it as our base evaluation metric to get both exactness and completeness of our classifier.

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