

Object Recognition in Computer Vision: Sketch-image Classification Challenge

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001 1. Introduction

002 In this report, I have provided my approach and experiments
 003 for the Sketch-image classification kaggle challenge, with
 004 results.

005 2. Approach and Experiments

006 I started with improving baseline and did few experiments
 007 and then I used two pre-trained models with different hyper-
 008 parameters. Throughout all experiments i used the dataset
 009 provided on kaggle. for my experiments. I make use of kag-
 010 gle notebook with GPU and github repository. Below i have
 011 given the details of what experiments i did, what accuracy i
 012 get with test set on kaggle and which challenges i faced and
 013 how i overcome those.

014 2.1. Experiments with Extended Baselines

015 Initially, I modified the baseline by adding convolutional
 016 layers. The architecture included 3 convolutional layers
 017 (kernels: 5, 5, 3), batch normalization, max pooling, an
 018 adaptive average pooling layer, a fully connected layer with
 019 dropout, and a final linear layer for classification[2]. With
 020 parameters (epochs=10, lr=0.001, batch size=32), the re-
 021 sults were poor (test error: 0.00135), performing worse than
 022 the baseline. This highlighted the limitations of extending
 023 simple baselines for complex datasets, So i didn't tried to
 024 do more experiments and moved to pre-trained model

025 2.2. Fine-Tuning DINOV2

026 I used pre-trained DINOV2 models (small, base, and
 027 large(registers) variants)[4]. The approach involved freez-
 028 ing the backbone and fine-tuning the classification head. I
 029 used dinov2 model using torch hub and optimizer AdamW,
 030 with cross entropy loss for those experiments[5].

031 2.2.1. Experiments

032 I did experiments with dinov2_vits14, dinov2_vitb14, and
 033 dinov2_vitb14_reg. For data augmentation i used two dif-
 034 ferent transforms:

035 1) Basic transformations: resized (224), normalize
 036 (mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]).

037 2) Extended transformation: resized(256), random re-
 038 sized crops(224,, scale=(0.8, 1.0)), rotations(15), and nor-
 039 malize (mean=[0.485, 0.456, 0.406], std=[0.229, 0.224,
 0.225])[3].

040 below is the different experiments with hyperparameters
 041 and results with dinov2, i keep changing batch size, learning
 042 rate, weight decay and no of epochs by observing the under
 043 and over-fitting during training. For simplification, I have
 044 only added improved results in Table 1.

Model Variant	Batch Size	Learning Rate	Epochs	Test Accuracy
dinov2_vits14	32	0.001	30	86.1%
dinov2_vits14	64	0.00141	30	86.3%
dinov2_vitb14_reg	64	0.00141	20	87%
dinov2_vitb14	128	0.001	20	90%

Table 1. Model configurations and results with Dinov2

046 2.3. Fine-Tuning Vit Vision transformer

047 After Dinov2, i also explored the Google ViT-base (Hug-
 048 ging Face) model and finetune[1] it on provided dataset. In
 049 experiments, i used both simple and extended data augmen-
 050 tation mentioned above. In Table 2, i added only the exper-
 051 iments where i get highest accuracy for that model.

052 2.3.1. Experiments

053 below table presents the results(test set) and hyperperame-
 054 ters used. here i also used Adamw optimizer with cross En-
 055 tropy loss, initially i observed it's overfitting so i changed
 056 my batch size and tried weight decay 0.001 to see if it im-
 057 proves overfitting, but it did improves only 1%.

Model Variant	Batch Size	Learning Rate	Epochs	Test Accuracy
vit-base-patch16-224	32	0.001	20	78.8%
vit-base-patch16-224	64	0.00141	20	78.2%

Table 2. Results with google/vit-base-patch16-224

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