Impact of transfer learning techniques in identifying the type of damage on an image for car insurance claims

Author: Ronald T. Nhondova
Lead TA: Nathan Inkawhich

Introduction

Claims processing for car insurance can be an administratively costly process, as the time (hence financial) investment required from claim adjusters can be intensive. Most expenses incurred by insurance companies are passed on to policyholders, so any process optimizations should be beneficial to both the company and the policyholder. The main objective of the project is to find the best candidate model to automate the classification of the location of damage on the car in a supplied image.

To achieve this, 3 transfer learning techniques are considered as follows:

- **Fixed Features** – were pre-trained model is used as feature extractor and only train last layer.
- **Finetune** – were pre-trained model weights are used for initialization and model finetuning is then carried out.
- **Hybrid** – is mixture of the above two methods, with first 50% of layers in pre-trained model having fixed weights and finetuning the remaining.

In addition, the effect of using either Stochastic Gradient Descent (SGD) or Adaptive moment estimation (ADAM) as optimizers, with various learning rates is observed for the above transfer learning techniques.

Data and Methodology

Figure 1. shows the distribution of the training images (9000+) and sample labelled images. The original dataset has 1500 images, but this has been supplemented with the Cars dataset (Krause et al., 2013) to ensure the model does not only learn identifying location but also if damage exists.

The pretrained models used are **ResNet18, ResNet50, Wide-ResNet50, SqueezeNet, ResNext101, VGG19 and DenseNet121**. The optimizers used are **SGD with momentum** and **Adam** with learning rates **0.1, 0.01** and **0.001**. Total number of models trained was 126 (25 epochs).

Figure 1: Distribution of training images by label and sample images.
Imbalanced dataset with no damage on most images and limited fender damage images.

Results

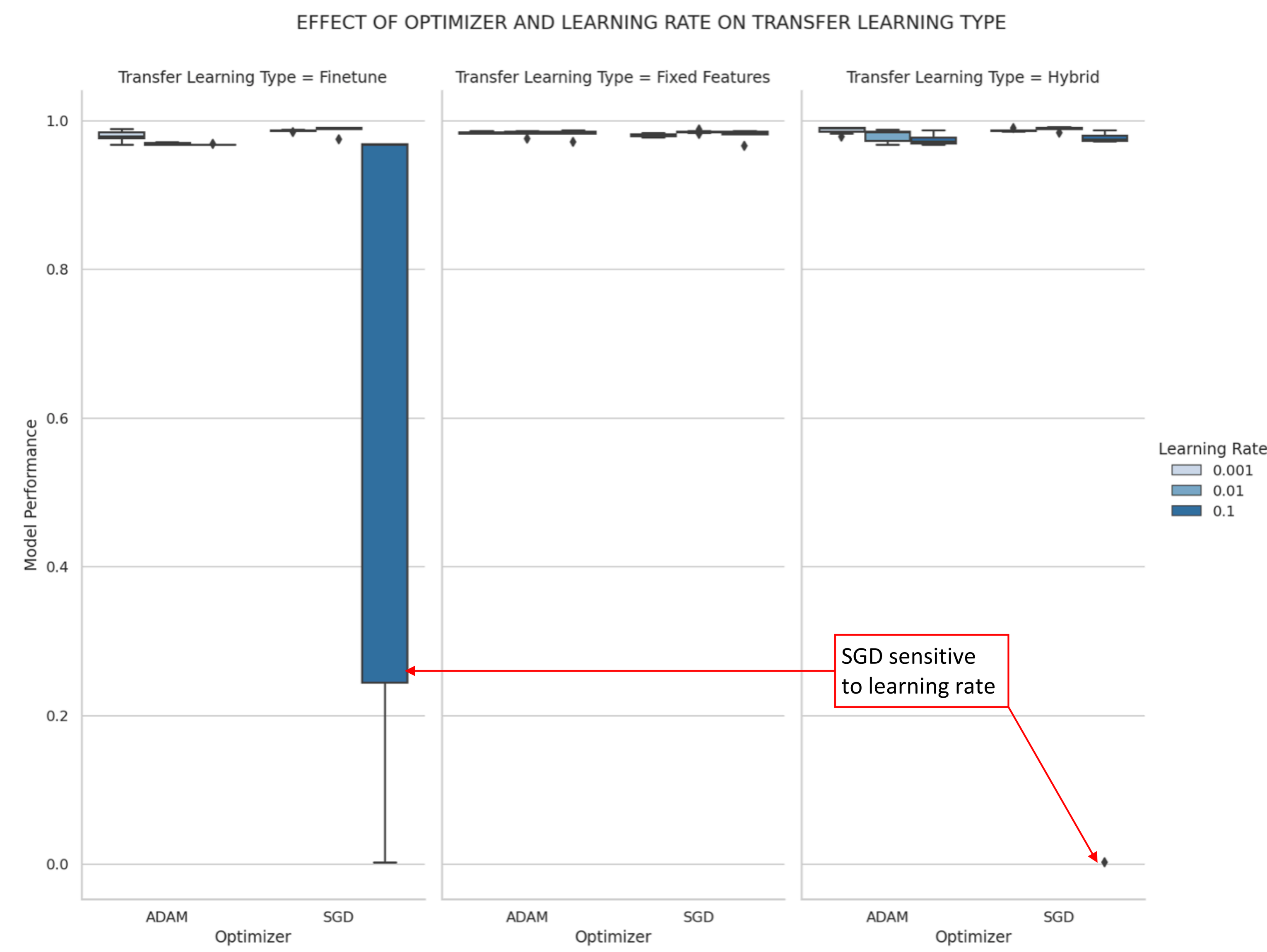

Figure 2: Model performance for different combinations of transfer learning technique, optimizer and learning rate.

Figure 2. compares the performance of the different transferring learning techniques. This highlights how SGD is sensitive to learning rate when finetuning of weights is involved (i.e. Hybrid and Finetune). ADAM seems to be robust and less sensitive to learning rate in comparison to SGD. When using pre-trained models as fixed features, models are not as sensitive to type of optimizer and learning rate chosen. Optimal results for finetuning are obtained when training smaller models like ResNet18.

All variations of transfer learning have consistent performance when ADAM is used. SGD with learning rate 0.01 results in best performance in most cases for each technique of transfer learning.

Table 1. shows the performance on the test set of the top 10 models . Wide ResNet50 based on hybrid transfer learning, is chosen as the final model based on performance.

Model Architecture	Transfer Learning Type	Optimizer	Learning Rate	Model Performance
wide_resnet50_2	Hybrid	SGD	0.010	0.9913
resnext101_32x8d	Hybrid	SGD	0.010	0.9912
resnext101_32x8d	Hybrid	ADAM	0.001	0.9910
densenet121	Finetune	SGD	0.010	0.9909
resnet50	Hybrid	SGD	0.010	0.9909
resnet50	Finetune	SGD	0.010	0.9909
densenet121	Hybrid	ADAM	0.001	0.9908
resnext101_32x8d	Hybrid	SGD	0.001	0.9903
resnet50	Hybrid	ADAM	0.001	0.9903
densenet121	Hybrid	SGD	0.010	0.9902

Table 1: Top-10 model performance for different combinations of transfer learning technique, optimizer and learning rate.

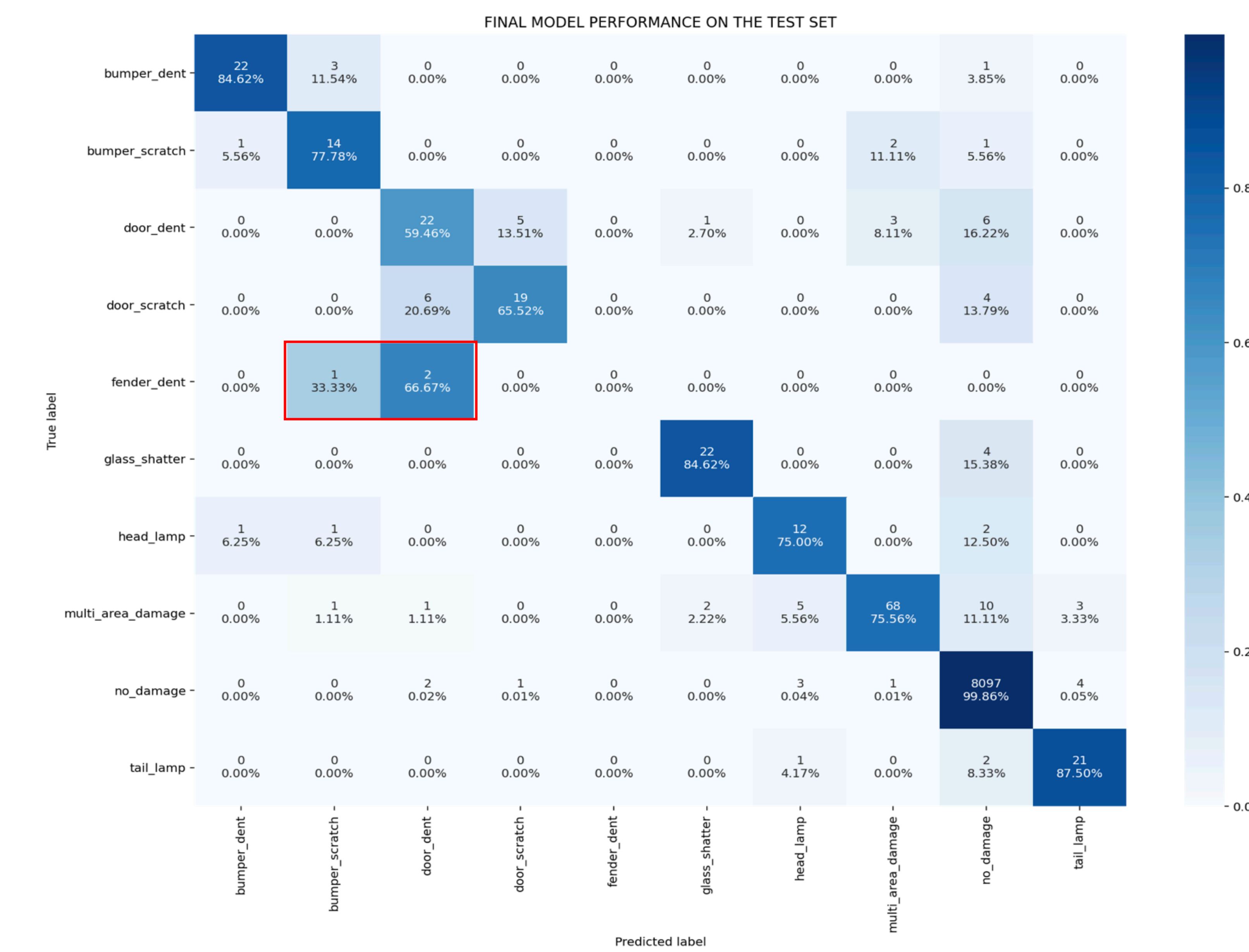

Figure 3: Confusion matrix of the final model performance with normalization by row.

Figure 3. is the confusion matrix for the final model, with the accuracy normalized by row. This highlights how the model performs well in identifying most classes except fender dents, which have insufficient samples in the training set and only 3 images for testing.

Conclusion and future work

The project highlights how the various transfer learning techniques perform given different optimizers and learning rates. Based on the results, ADAM seems is the ideal optimizer when consistency in performance is required but with SGD giving best results with the ideal learning rate (0.01 being a good starting point). Using a hybrid approach resulted in the best model.

The resulting final model currently performs sufficiently well, but further improvements by collecting more images might be obtained, if performance uplift required.

References

Krause et al. (2013). "3D Object Representations for Fine-Grained Categorization." In: 4th International IEEE Workshop on 3D Representation and Recognition (3dRR-13).

Nathan Inkawhich (2017). "Finetuning torchvision models." In: https://pytorch.org/tutorials/beginner/finetuning_torchvision_models_tutorial.html.