Car Damage

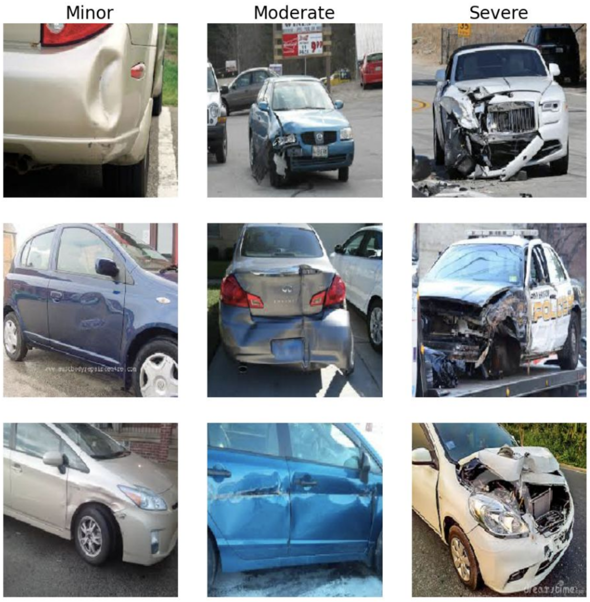
Learning to automatically classify damage on a vehicle as minor, moderate or severe via Transfer Learning

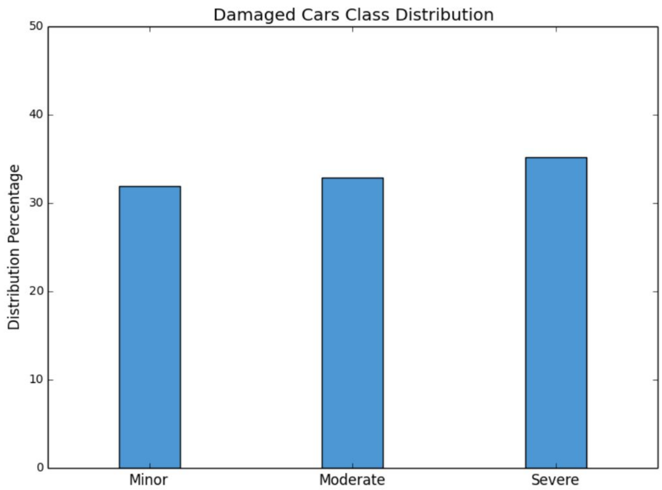
Motivation

Simple & fast insurance claims

Automatic classification of on-road accidents

Dataset (1291 Images)





Technical Approach

- A multi-class classification problem. Accuracy & F1 score used to measure the performance of the models
- Transfer learning used since the amount of available data was limited
- Used VGG 16 Pre-trained on Imagenet for all the experiments. Implementation was done in Pytorch

Classification

Mudit Bhargava
mbhargava@cs.umass.edu

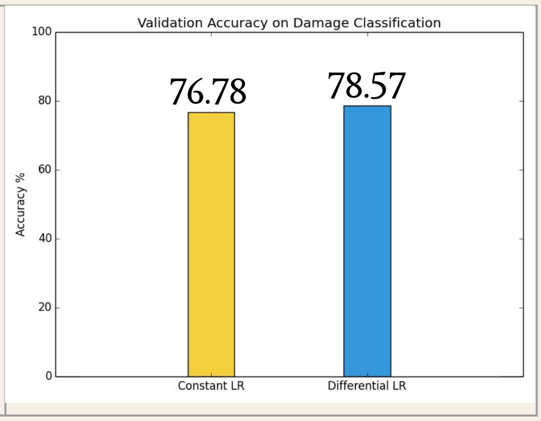
Experimental Setup

Train Data (76.5%) Boosted with data augmentation	Val Data (8.5%)	Test Data (15%)

- Stopping Criteria: Model is saved if there is an increase in validation accuracy at the end of any epoch
- Model ensembles were used to report final results

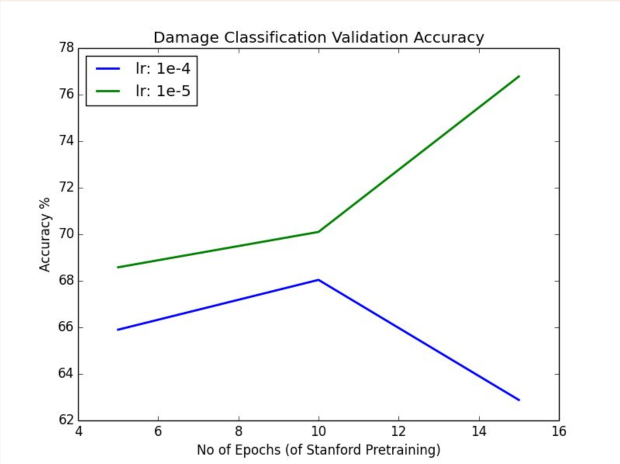
Differential Learning Rates

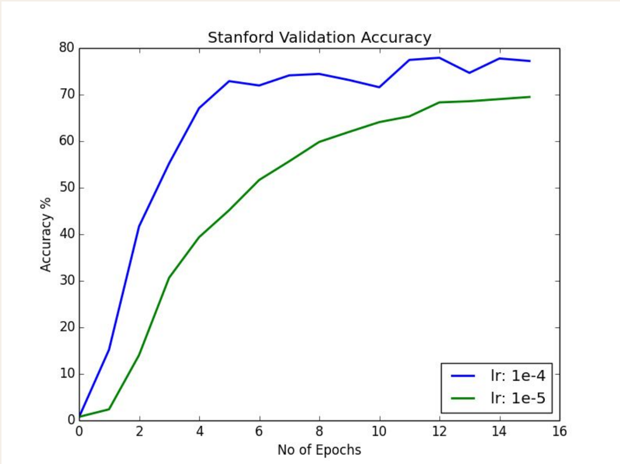
- Different layers in the model assigned different learning rates
- Intuition: Different layers need different degree of fine-tuning e.g Conv layers vs Last classification layer



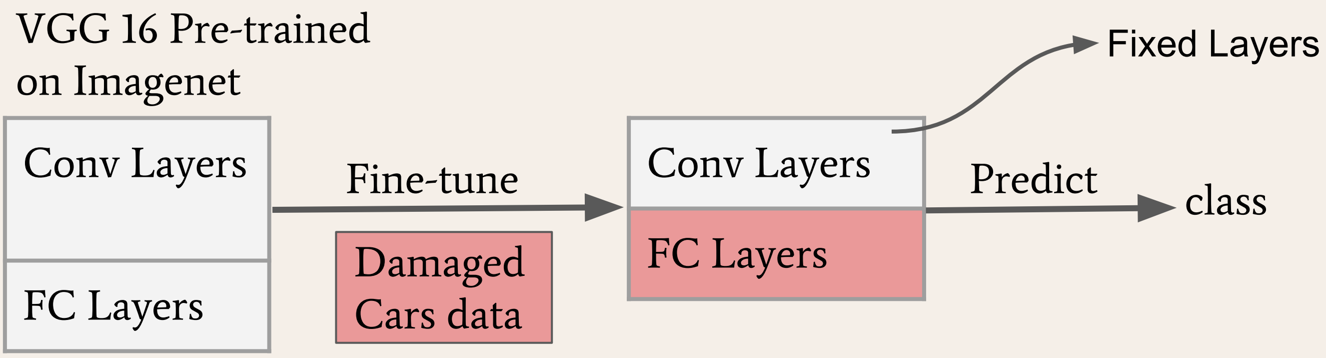
Effect of Stanford Fine-tuning

- Degree of Stanford fine-tuning affects the damage classification results
- Higher accuracy on stanford does not correspond to higher validation accuracy on damage classification

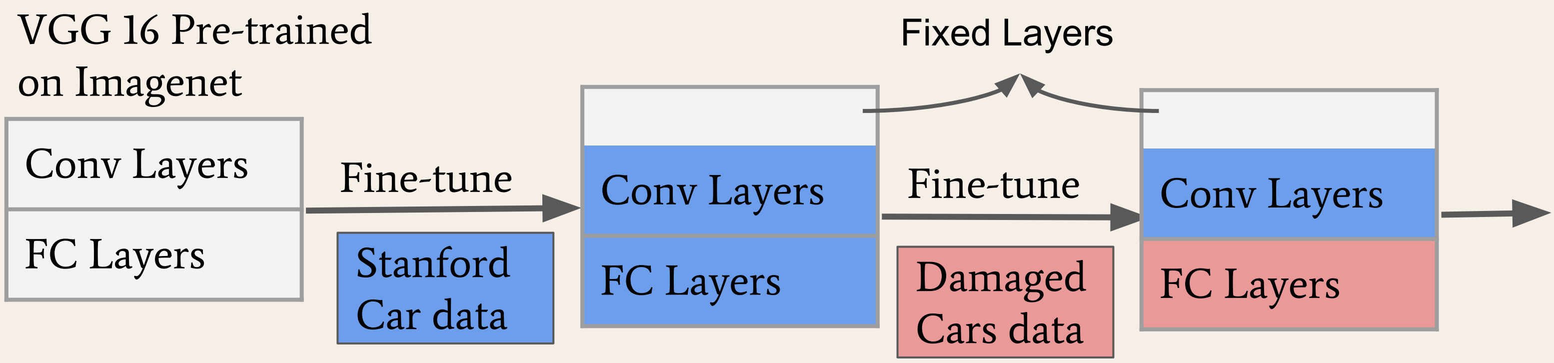




Transfer Learning: Traditional Approach



Transfer Learning: New Approach



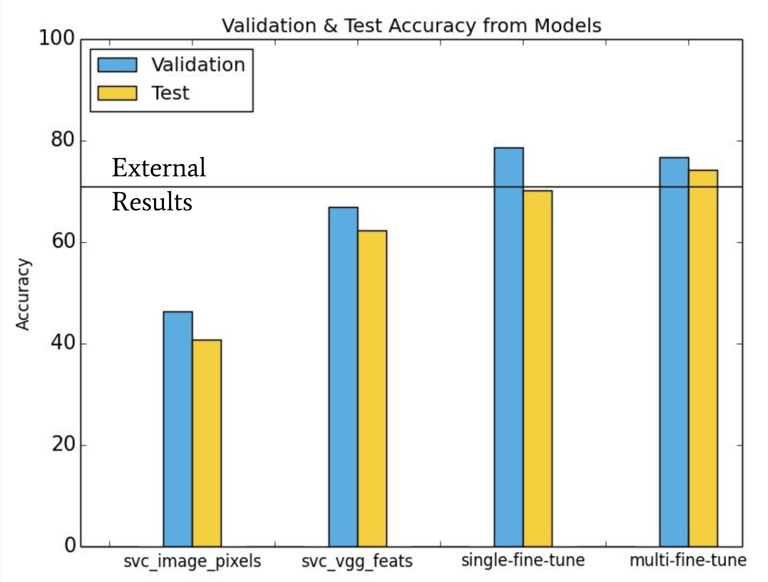
- Due to the small size of damaged car dataset, fine-tuning on this dataset was restricted only to fully connected layers of VGG 16
- For pre-training on Stanford car dataset (~16,000 images) all the layers from layer 4 onwards were fine-tuned

Future Work

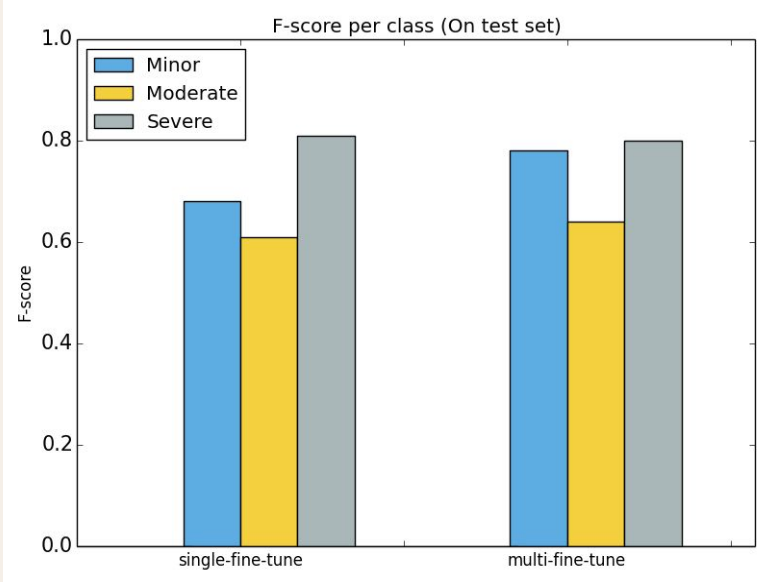
- Explore possibility of validation on damaged car dataset while fine-tuning on Stanford car dataset
- Explore possibility of joint fine-tuning (e.g alternate) of Stanford car dataset & Car damage dataset.
- Explore the impact of differential learning on Stanford pre-training
- Increase diversity and quantity of damaged car data

Accuracy & F1 score

Accuracy



F1 score



Result Analysis

	Minor	Moderate	Severe
Correct			
	Predicted as Severe	Predicted as Severe	Predicted as Moderate
Incorrect			

Conclusion

- Any form of fine-tuning helps boost the classification accuracy as compared to baseline feature extraction
- Pre fine-tuning on stanford car dataset and differential learning rates lead to a slight improvement in performance
- Extent of fine-tuning on Stanford car dataset affects performance on damage classification task
- One should be careful when mixing datasets