

Traffic Sign Classification using Convolutional Neural Networks

COMP 6721 - Fall 22
Group H

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PROBLEM STATEMENT AND ITS IMPORTANCE

Traffic Sign Classification is the process of automatically recognizing traffic signs in the given image/frames of images.

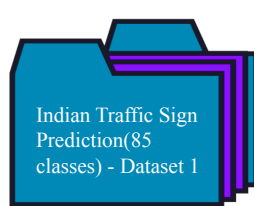
- ❑ Its major use case is to solve the problem of accidental loss of life and property, by increasing the driver's focus using automatic detection of traffic signs on the way.
- ❑ With automotive industry being significantly inclined towards expanding the scope of autonomously driven systems, they need features that make it capable of sensing its environment and operating without human involvement. Hence, it introduces dependency on such traffic sign classifiers to follow the traffic rules properly.

CHALLENGES FACED AND GOALS OF THE APPLICATION

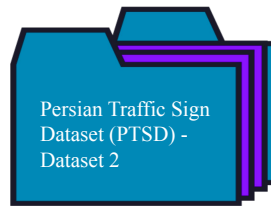
- ❑ Some of the major challenges faced by the existing the problem in general are:
 - ❑ the changes in illumination in the captured sign images, weather conditions, occlusion, damages to the signs, cascade of the traffic signs
 - ❑ the standard priority signs adopted internationally differ in shape, color, and border
- ❑ The goal behind this application is to aim at providing a solution keeping in mind the challenges by :
 - ❑ comparing the performance of different CNN architectures in classification of different traffic signs against datasets of varying classes and samples.
 - ❑ analyze the effects of different hyperparameters and give a comprehensive comparative analysis of the results.



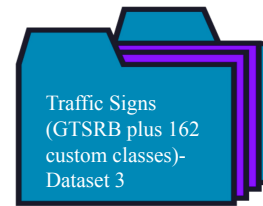
Datasets



No. of Classes : 15
Training Samples : 2617
Test Samples : 710
Image size : max. 3192 x 1400
min. 13 x 11



No. of Classes : 12
Training Samples : 7956
Test Samples : 1228
Image size : max. 4608 x 3456
min. 42 x 50



No. of Classes : 8
Training Samples : 13984
Test Samples : 4590
Image size : max. 4608 x 974
min. 22 x 44

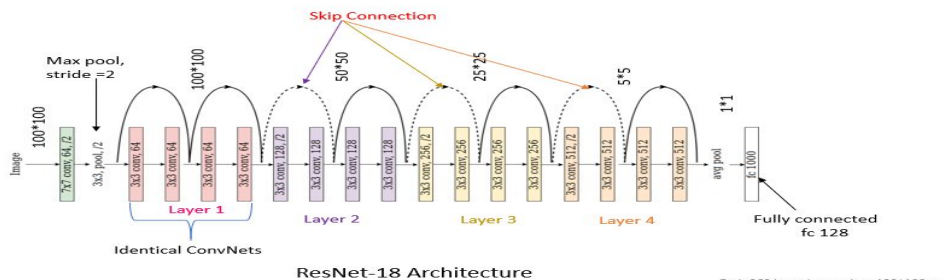
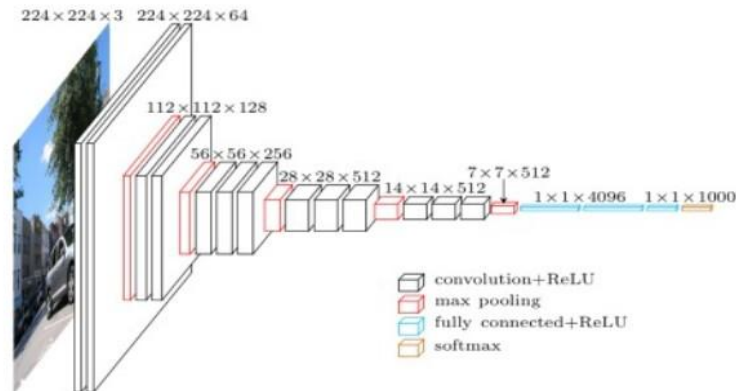
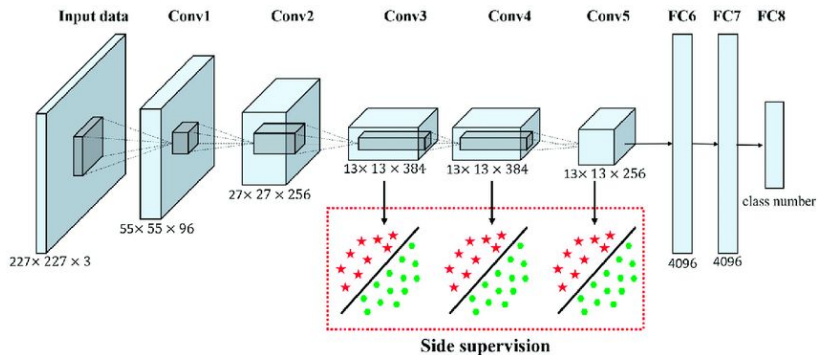
Classes Imbalance Handled : Weighted Cost Function

- **Pre-processed to a Standard Size :** 224 x 224
- **Augmentation Techniques :**
ColorJitter(brightness(0.5, 1.2)) ,
RandomHorizontalFlip, RandomAdjustSharpness.
- **Normalization:** mean=[0.485, 0.456, 0.406],
std=[0.229, 0.224, 0.225]



Methodology

AlexNet, VGG-11 and ResNet-18: the chosen architectures.



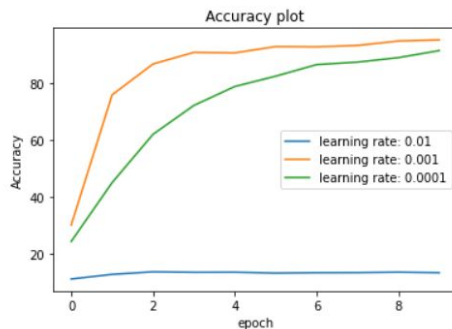
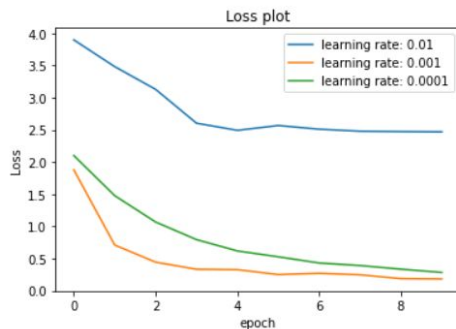
Fruit 360 Input Image size= 100*100 px

- All the 3 architectures were trained against the 3 datasets without transfer learning to get 9 models with fixed set of hyperparameters
- Additionally 2 models trained with AlexNet and ResNet-18 on dataset 1 with transfer learning.
- Hyperparameters choice: batch size =32, weighted cross entropy as the loss function and a learning rate of 0.0001. Input image size 224x224 epochs to 10, optimizer Adam
- Model performance evaluated after every 10 batches and validated against the validation set
- Hyper parameter tuning done to pick the best learning rate and retrained all the 11 models
- These models are then evaluated on various performance parameters such as their training accuracy, accuracy on validation and test dataset, F1-score, precision, recall and AUC score metrics.
- TSNE plots can be used to understand high dimensional data and project it into low dimensional space like 2D or 3D.
- Detailed comparison is done after the completion of training. Performance results shown ahead.

Results - 9 Models

		AlexNet	VGG-11	ResNet-18
Dataset 1	Train Acc.:	53.12%	65.62%	62.50%
	Test Acc.:	46.90%	57.32%	53.09%
	Test F1:	0.46	0.57	0.53
Dataset 2	Train Acc.:	84.38%	93.75%	90.62%
	Test Acc.:	86.72%	85.26%	79.64%
	Test F1:	0.86	0.85	0.79
Dataset 3	Train Acc.:	65%	84.3%	80%
	Test Acc.:	75.14%	79.23%	61.80%
	Test F1:	0.75	0.79	0.61

Before Hyper-Parameter Tuning



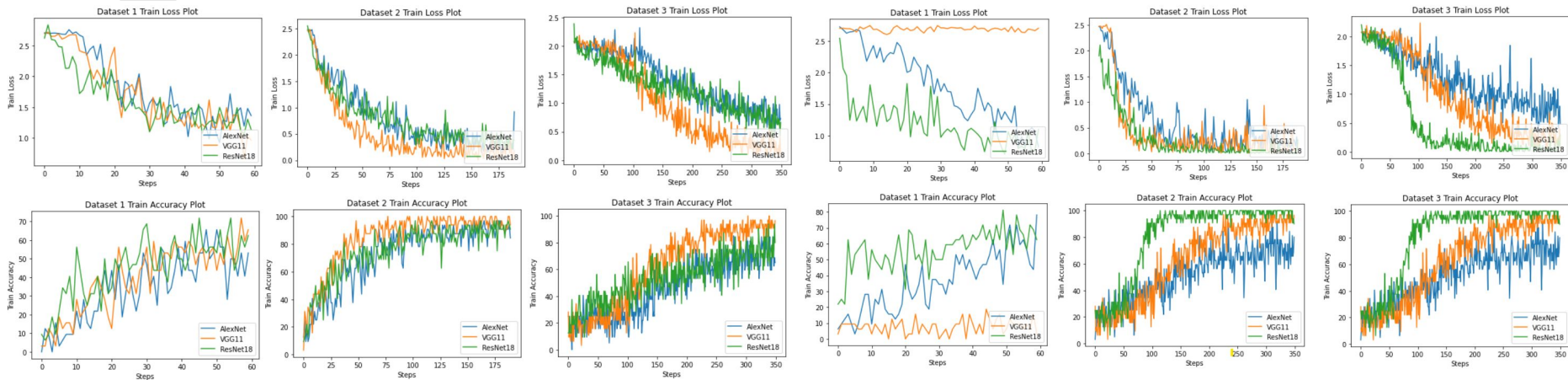
Hyper-Parameter Tuning on Learning Rate

	On Test	AlexNet	VGG-11	ResNet-18
Dataset 1	Acc.:	55.21%	11.4%	62.25%
	F1:	0.55	0.11	0.62
	Precision:	0.63	0.007	0.66
	Recall:	0.59	0.07	0.65
	AUC:	0.07	0.5	0.10
Dataset 2	Acc.:	91.78%	95.11%	96.42%
	F1:	0.91	0.95	0.96
	Precision:	0.90	0.94	0.95
	Recall:	0.93	0.95	0.97
	AUC:	0.08	0.06	0.09
Dataset 3	Acc.:	80.13%	91.98%	95.77%
	F1:	0.80	0.91	0.95
	Precision:	0.79	0.93	0.96
	Recall:	0.79	0.92	0.95
	AUC:	0.28	0.21	0.19

	On Test	AlexNet	ResNet-18
Dataset 1	Acc.:	75.77%	70%
	F1:	0.76	0.7
	Precision:	0.85	0.74
	Recall:	0.79	0.71
	AUC:	0.05	0.19

After Hyper-Parameter Tuning

Comparison - 9 Models



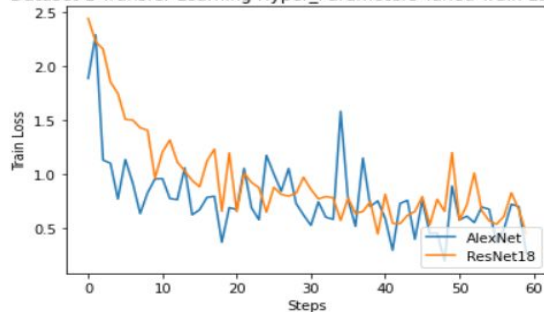
Before Hyper-Parameter Tuning

After Hyper-Parameter Tuning

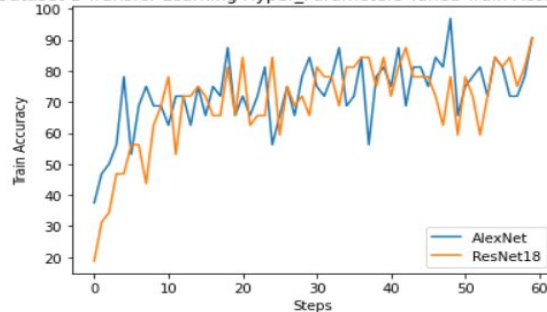
Comparison - Transfer Learning Model before and after Hyper-Parameter Tuning



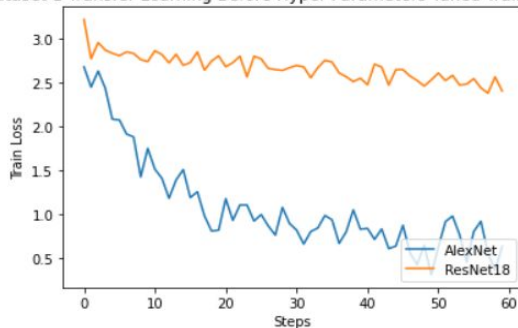
Dataset 1 Transfer Learning Hyper_Parameters Tuned Train Loss Plot



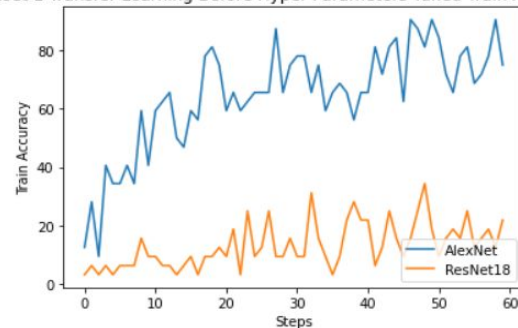
Dataset 1 Transfer Learning Hyper_Parameters Tuned Train Accuracy Plot



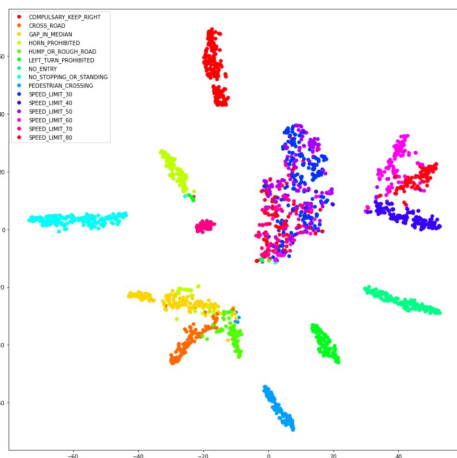
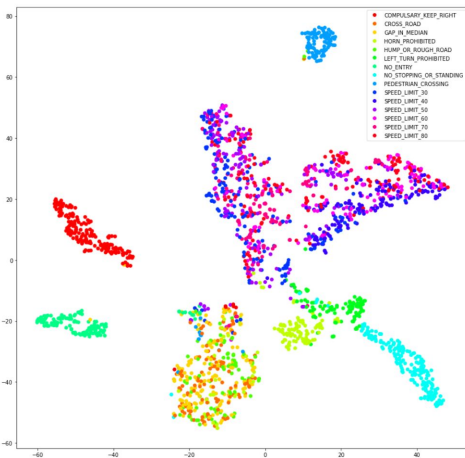
Dataset 1 Transfer Learning Before Hyper-Parameters Tuned Train Loss Plot



Dataset 1 Transfer Learning Before Hyper-Parameters Tuned Train Accuracy Plot

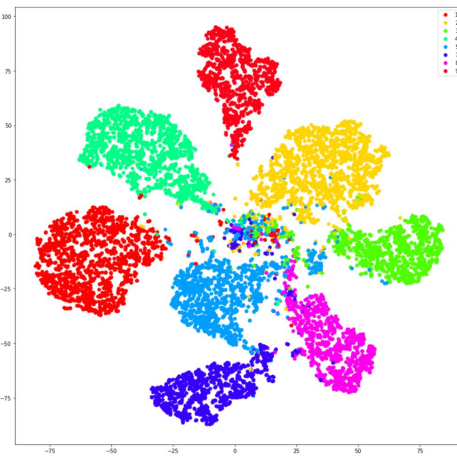
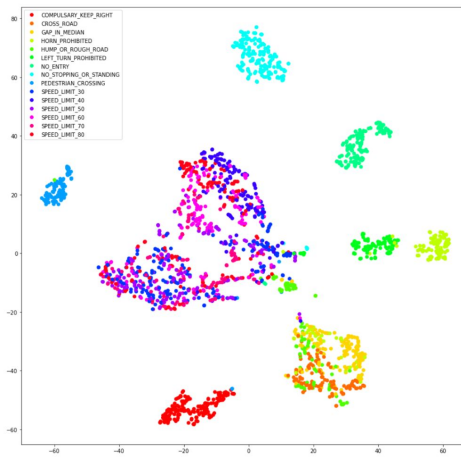


T-SNE Visualization



**T-SNE Architecture Visualization
for AlexNet Model**


Without Transfer Learning (Left)
With Transfer Learning (Right)



**T-SNE Dataset Visualization for
ResNet-18 Model**

Dataset 1 - Small Dataset (Left)
Dataset 3 - Large Dataset (Right)

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