DL PROJECT REPORT

Proposal for Comparison of different models for Traffic Detection

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Abstract : The Goal of our project is to use different models for Traffic Detection. For this purpose we are implementing the Student-Teacher model in which we have used Resnet18 pre-trained model to train our teacher network and for further experiment we have used Student model with knowledge distillation and also applied Ensembling on Student model. Apart from these we have also used Transfer Learning. Also we have widely used image processing techniques and applied above models

Introduction : We have proposed a deep learning project on the topic '**Comparison of different models for Traffic Detection**.' Motivation behind using this topic is that our model works in collaboration with object detection models and can be useful to identify these different classes from live CCTV footage. This can be further used to generate an alarm so as to resolve the scenario.

Dataset Analysis : The dataset that we have used is TrafficNet dataset which contains images of traffic. It contains 4,400 images that have 4 classes which are 'Accident', 'dense traffic', 'sparse traffic' and 'fire' each of these classes contain 1,100 images where 900 images are for training and 200 images for testing dataset for each class.

Methodologies :

First, we have implemented knowledge distillation using resnet18 as a Teacher model. A student-teacher model is a type of knowledge distillation model where a smaller model the "student" is trained to mimic the outputs of a larger and more complex model the "teacher". The idea is to transfer the knowledge learned by the teacher model to the student model in order to improve the student's performance.

Second, we have used an ensemble of student networks learned by a common teacher in which we have created 5 models for student models with different hyper-parameters (number of epochs and learning rate).

Third, we have implemented Transfer Learning using VGG16. Transfer learning is a machine learning technique where a model that has been trained on a specific task is reused as a starting point for training a new model on a different but related task.

Also we have used image processing like binary thresholding to see and compare result with normal images.We have employed different deep learning techniques to successfully train different models.

Results :

Training loss and accuracy for teacher model	Training loss and accuracy for student model
[Epoch 1] loss: 0.885, acc: 67.889	[Epoch 1] Average Loss: 4.0891
[Epoch 2] loss: 0.524, acc: 81.556	[Epoch 2] Average Loss: 4.1121
[Epoch 3] loss: 0.408, acc: 85.861	[Epoch 3] Average Loss: 4.1345
	Student Model Accuracy on Test Images: 27 %

Training loss and accuracy for student model with ensembling

[Model 1 Epoch 1] Average Loss: 1.8523	[Model 3 Epoch 2] Average Loss: 0.8107
[Model 1 Epoch 2] Average Loss: 1.8581	[Model 4 Epoch 1] Average Loss: 0.1464
[Model 2 Epoch 1] Average Loss: 1.0924	[Model 4 Epoch 2] Average Loss: 0.1500
[Model 2 Epoch 2] Average Loss: 1.0876	[Model 5 Epoch 1] Average Loss: 2.1402
[Model 3 Epoch 1] Average Loss: 0.8029	[Model 5 Epoch 2] Average Loss: 2.1279

Transfer learning model

Epoch - 1 Epoch 1 loss: 2.194

Epoch - 2 Epoch 2 loss: 1.151

Fine Tuning

Epoch - 1 Epoch 1 loss: 1.024

Epoch - 2 Epoch 2 loss: 0.890

Epoch - 3 Epoch 3 loss: 0.805

Accuracy of the network on the test images: 89 %

When images are processed with binary thresholding -

Training loss and accuracy for teacher model	Training loss and accuracy for student model
[Epoch 1] loss: 1.057, acc: 58.611	[Epoch 1] Average Loss: 2.2290
[Epoch 2] loss: 0.781, acc: 70.583	[Epoch 2] Average Loss: 2.2429
	Student Model Accuracy on Test Images: 26 %

Training loss and accuracy for student model with ensembling

[Model 1 Epoch 1] Average Loss: 1.4744	[Model 3 Epoch 2] Average Loss: 1.7494
[Model 1 Epoch 2] Average Loss: 1.4753	[Model 4 Epoch 1] Average Loss: 2.0395
[Model 2 Epoch 1] Average Loss: 1.6279	[Model 4 Epoch 2] Average Loss: 2.0316
[Model 2 Epoch 2] Average Loss: 1.6204	[Model 5 Epoch 1] Average Loss: 4.2656
[Model 3 Epoch 1] Average Loss: 1.7558	[Model 5 Epoch 2] Average Loss: 4.2696

Transfer learning model

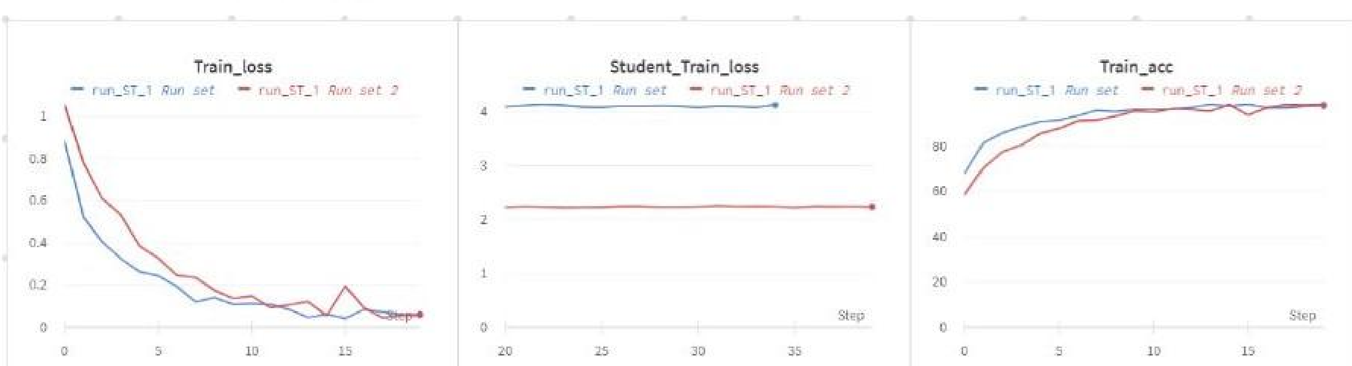
Epoch - 1 Epoch 1 loss: 1.307   Fine Tuning Epoch - 1 Epoch 1 loss: 1.020

Epoch - 2 Epoch 2 loss: 1.163   Epoch - 2 Epoch 2 loss: 0.925

Epoch - 3 Epoch 3 loss: 0.890

Accuracy of the network on the test images: 68 %

Plots showing various models comparison -



Comparisons/Conclusions :

By comparing the results obtained for different models we observe that the teacher model trains with high accuracy but while the student model is used to mimic teacher model. It is not giving satisfactory results like accuracy only 27%. When we use this after processing the images using binary threshold, this model gives accuracy for training more while for the student model it is still 26% only . It decreases because our images are losing some features.

Also we used Transfer learning for both the cases in which accuracy is much better. It is 89% for the first case and 68% for the second case.We have also used ensembling for student models with different hyper-parameters but still it did not give significant results. All rest of comparisons can also be seen from plots provided.

Summary :

We can summarize based on the results that by implementing the student teacher model and transfer learning which are a part of the deep learning techniques, further strengthens the scope for this project.By analyzing large datasets of traffic images and videos models can automatically detect and track vehicles, pedestrians and other relevant objects.This system can be further integrated to other technologies such as sensors, camera etc. to enhance the overall efficiency of the transportation network.Overall, the use of deep learning models in traffic detection has the potential to transform the way we manage traffic, making our roads safer and more efficient for everyone.

Future Scope :

This project has a promising future scope considering the increasing need for smart traffic management systems.As new techniques and models are developed they can also be incorporated into our model to further improve the efficiency and accuracy to replicate the real time scenarios.This model can further be extended to include more classes and more diverse datasets.It can further be implemented in surveillance and other security applications.

Demonstration link -

https://drive.google.com/file/d/1jWc6UsawI-Ls2x19z7G5a8n40i24bSVr/view?usp=share_lin