Accident Detection On the Edge

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Outline

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- 2. Data Overview
- 3. Training
- 4. Testing
- 5. Demo
- 6. Error Analysis
- 7. Challenges
- 8. Final Thoughts
- 9. Q&A



Problem Statement

 Build an accident-detection algorithm for surveillance cameras and deploy a prototype on an edge device





Inspiration

- Survival rate dependent on Emergency Response
- Hit-and-run incidents rising with higher fatalities
- More traffic cameras means less attention span
- Automated notifications can assist monitoring
- Improve emergency response time

1.3 mn

Yearly fatalities caused by car accidents globally

30%

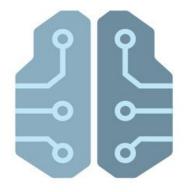
Higher fatality rates for hit-and-run accidents 50 mn

Surveillance cameras in the US

Operationalization Tools

- Supervised Learning
- Binary Image Classification
- Transfer Learning

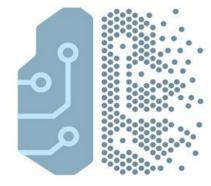
- Google Cloud Platform Compute and Cloud Storage
- **IBM SoftLayer** P100 GPUs
- NVIDIA: DIGITS & Transfer Learning Toolkit
- Edge: NVIDIA Jetson TX2 and Logitech USB C270 Camera
- Others: Google Vision API, ffmpeg



Artificial Intelligence



Machine Learning

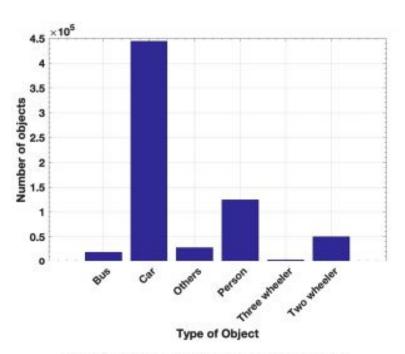


Deep Learning

Dataset

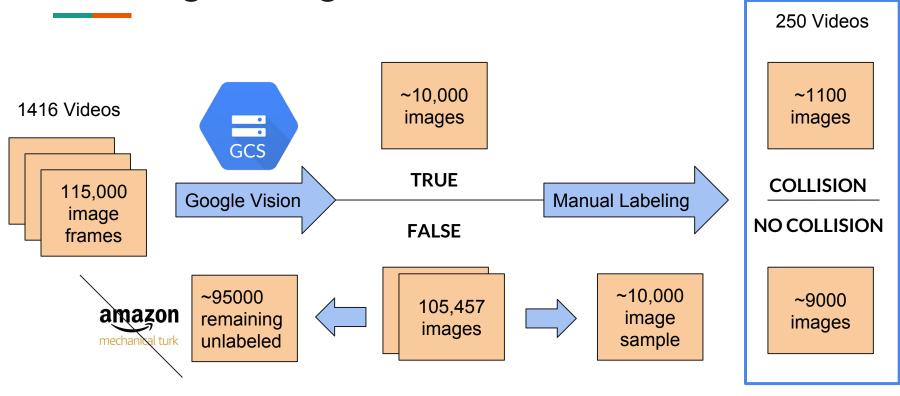
- Road Collision Videos: sourced from Youtube
- Collated by Ankit et al, Carnegie Mellon University
- 5.2 hours of footage
- 45GB
- 1,416 videos
- 518,256 extracted video frames
- Variety of weather and lighting amongst frames



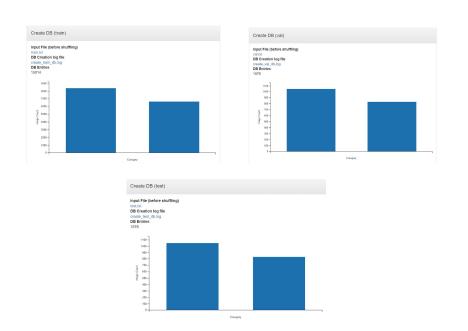


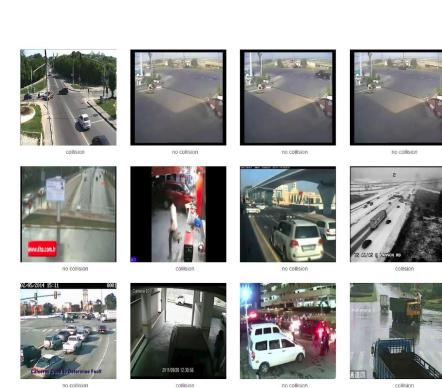
(a) Number of objects by categories

Data Engineering and Annotation



Exploring The Data





Training

- **APPROACH:** Transfer Learning via Pretrained Models
- FRAMEWORK: DIGITS, Tensorflow, and Nvidia Transfer Learning Toolkit
- MODEL ARCHITECTURE: ResNet18, ResNet50, VGG-16, Inception v3 and Googlenet

FRAMEWORK





TOOLKIT



NGC TLT DIGITS

TENSORFLOW

MODEL ARCHITECTURE

GOOGLENET

RESNET-18 RESNET-50 VGG16

INCEPTION-V3

DEPLOYMENT



JETSON DL SDK

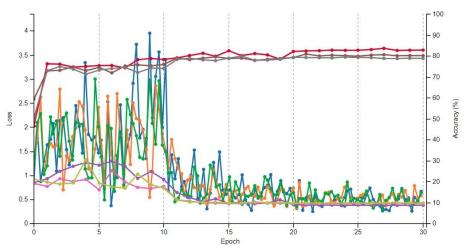
Training

- GOOGLENET: Retraining all the layers outperforms
- **EPOCHS:** 10-30; **OPTIMIZER:** SGD; **LEARNING RATE:** 0.005 0.01

LEARNING CURVE: GOOGLENET (UNFIXED LAYERS)

30 accuracy (val) 97.1928 loss (val) 0.0811788 loss1/accuracy (val) 95.55080000000001 loss2/accuracy (val) 96.6631 loss2/accuracy (val) 0.085546

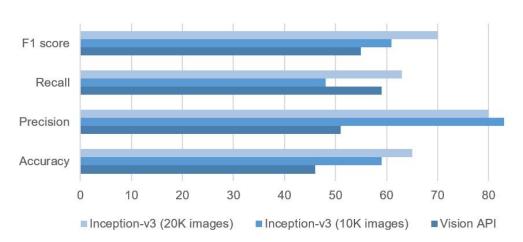
LEARNING CURVE: GOOGLENET (FIXED LAYERS)



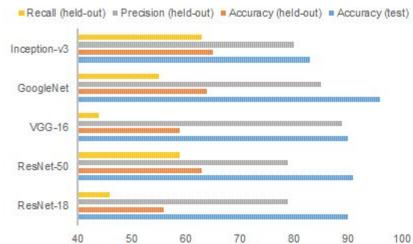
Validation and testing

- Baseline Vision API: 45% accuracy
- Recall rates improve by 15% as data doubles
- Inception V3 has the highest f1 score @ 0.7; Googlenet has the highest precision at 89%

EFFECT OF DATA SIZE ON MODEL PERFORMANCE



ARCHITECTURE-WISE MODEL PERFORMANCE



Error Analysis

- Post-impact
- Motorcycles
- Edge of frame











Googlenet: Signs of Improvement

- We see an improvement in detecting these incidents
- Although, we believe there is room for improvement here





Predictions:

Collision 94.81% No collision 5.19%



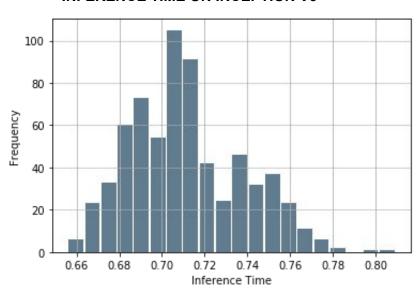
Predictions:

Collision 92.17% No collision 7.83%

Inference Time



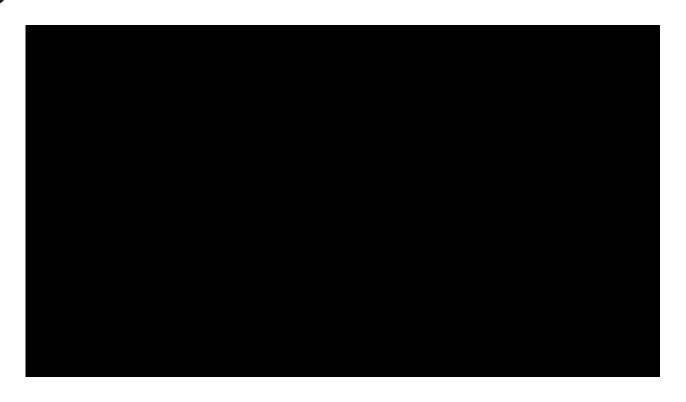
INFERENCE TIME ON INCEPTION V3



REAL-TIME INFERENCE USING JETSON TX2



Demo



Real-time



Challenges

- Need More Data: data augmentation could assist
- HIT Was A Miss: Human Intelligence Tasks (on MTurk) saw 32% errors in two-class labelling
- Unintentional Bias: caused by semi-supervised labelling (Vision API) towards motorcycles
- Err On The Side Of Caution: need higher recall rates
- Inference Time: For the best model (Inception V3), the fastest frame rate is 1fps

Discussions & Further Work

- Decision Support vs. Automated Solution
- Multi-Class Approach: to evaluate solution's impact and post-impact performance
- Background Subtraction: Focus on what matters
- Video Understanding: Anomaly Detection Using Video Embeddings



Concluding Remarks

- Transfer Learning outperforms baseline across all model architectures
- More data means more accuracy (especially recall rates)
- Model Performance: High precision; Low recall rates
- Inception-v3: highest f1 score; Googlenet: highest precision
- Video Understanding (through video embeddings) vs. Frame-level Image Classification
- Inference Time: best model has inference time of 0.7 sec/frame



Q&A