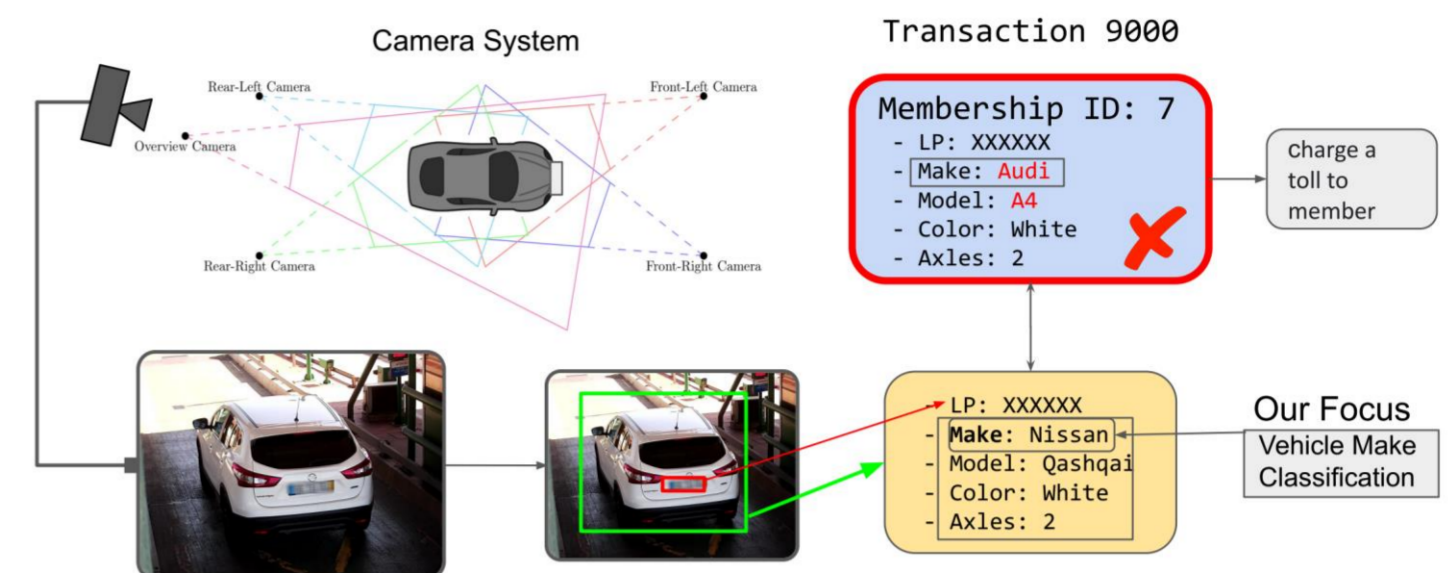


Deep Learning on Intelligent Transportation Systems

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Motivation

- Automatic toll collection (ATC) applications mostly use vehicles' unique registered RFID devices to execute toll transactions. Because these devices are not embedded in the vehicles, infractions can occur when attached to other vehicles resulting in improper tolling transfers.
- To enrich the verification process, visual vehicle characteristics, e.g. vehicle's make, model, colour, number of axles, etc, could be used.
- Problems: camera trigger errors, illumination, occlusions, etc.



Goal

- Design a Convolutional Neural Network (CNN) architecture capable of exploiting images provided by different cameras
- Improve vehicle make classification with multiple views of the same vehicle



Related Work

- Fine-grained visual classification
- Fine-grained vehicle classification
- Multi-View Classification



ATC Multi-View Dataset

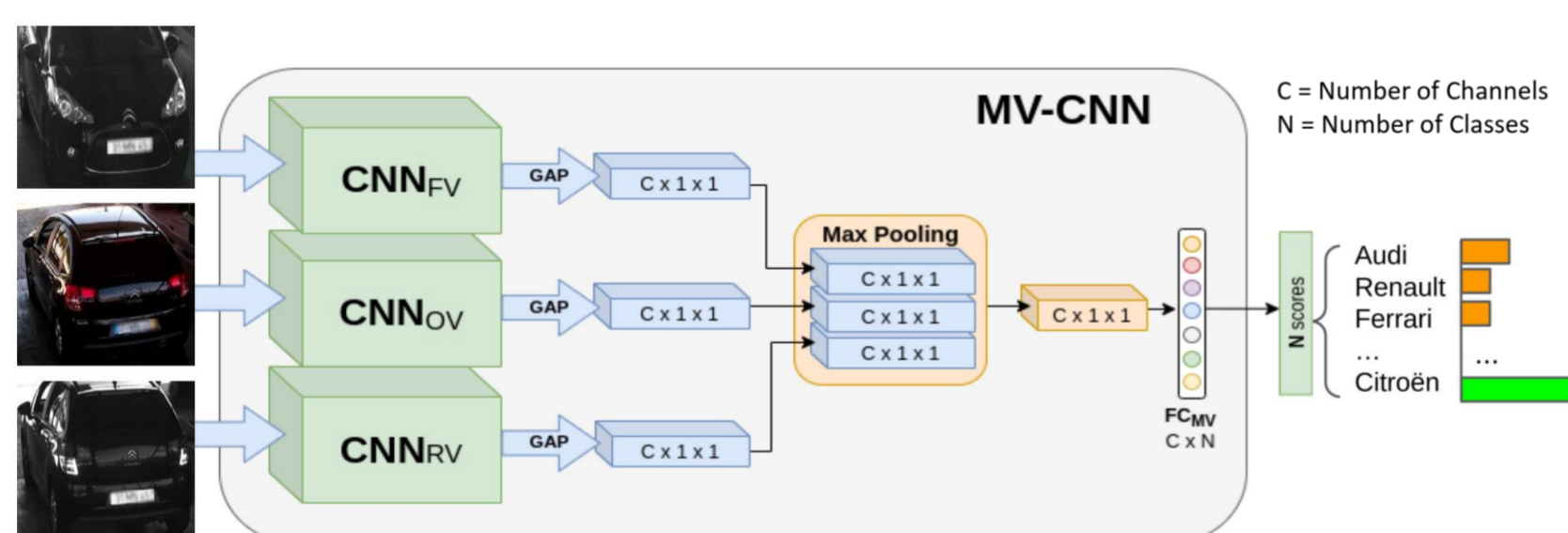
- No Public Dataset Available: Construct our own private dataset
- Images captured from 2 sites: 8367 Vehicle Transactions
- 3 Views per Transaction:
 - Front-Left View (F) [IR] / Rear-Left View (R) [IR] / Overview (O) [RGB]
- 38 Vehicle Makes and Bounding Box Annotations
- Hard subset: more challenging test set with 15 vehicle makes

Our approach

- CNN architecture** that receives input images from different views of the vehicle and extracts features for each view.
- Late fuse (max)** approach to aggregate all views' features into a single enhanced descriptor for vehicle's make classification

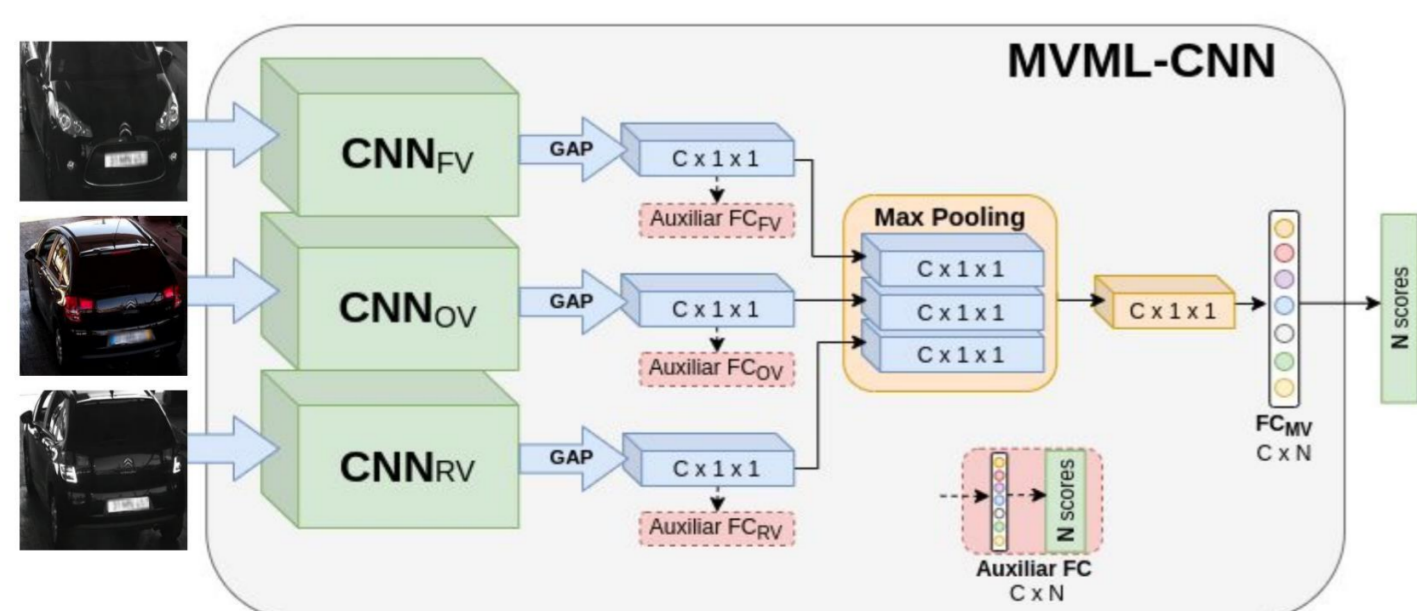
Multi-View Classifier

- End-to-End Learning
- CNN weights can be shared (MV-S) or nonshared (MV)
- Loss: Cross-Entropy



Multi-View and Multi-Loss Classifier

- Auxiliary Classifiers for each view during training
- CNN weights can be shared (MV-ML-S) or nonshared (MV-ML)



- Multi-loss Function: $loss = loss_{MV} + \alpha \sum_{i=1}^{N_v} loss_{SV_i}$

Experimental Evaluation

- Comparison between Single-View (SV) and Multi-View (MV)
- Experiments with different view combinations
- Training images were subject to an *ad hoc* data augmentation that includes colour, affine, and erase operations.
- MV and MV-ML branches: ResNet 18 CNN

ATC Dataset

- 5860 train
- 1673 validation
- 834 test

Classification results in Accuracy [%]

Cfg \ V	F	R	O	F-R	F-O	All
DenseNet	94.84	89.09	89.45	—	—	—
Inception	94.48	88.49	89.45	—	—	—
ResNet-18	93.76	85.61	88.13	—	—	—
ResNet-50	94.00	89.09	88.85	—	—	—
MV	—	—	—	94.48	95.08	95.20
MV-S	—	—	—	93.88	94.36	95.68
MV-ML	—	—	—	94.60	95.68	95.20
MV-ML-S	—	—	—	93.88	94.48	95.32

ATC Dataset (Hard)

- 497 test

Cfg \ V	F	R	O	F-R	F-O	R-O	All
DenseNet	49.10	57.34	77.67	—	—	—	—
Inception	53.52	58.95	80.28	—	—	—	—
ResNet-18	48.29	41.85	68.61	—	—	—	—
ResNet-50	50.70	47.08	76.26	—	—	—	—
MV	—	—	—	55.33	64.79	39.84	64.39
MV-S	—	—	—	53.12	73.04	69.82	74.45
MV-ML	—	—	—	59.16	74.04	50.70	75.05
MV-ML-S	—	—	—	61.37	77.06	74.45	80.89

- Competitive and improved performance compared with SV CNNs.
- More robust in challenging scenarios where discriminative views are affected by acquisition problems and clear gains compared with same SV architecture branch (12%).

Qualitative Results - ATC Dataset (Hard)



References and Support

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