Caltech Pedestrian Dataset: Evaluated Algorithms

		features	classifier	training	notes
ACF	[20]	channels	AdaBoost	INRIA	evolution of ChnFtrs [source code]
ACF++	[37]	channels	AdaBoost	Caltech	
ACF-Caltech	[20]	channels	AdaBoost	Caltech	evolution of ChnFtrs [source code]
ACF-Caltech+	[36]	channels	AdaBoost	Caltech	uses deeper trees and denser sampling
ACF+SDt	[47]	channels	AdaBoost	Caltech	SDt = Stabilized Dt (motion features)
AdaptFasterRCNN	[69]	pixels	DeepNet	Caltech+	ImageNet+CityPersons data
ADM	[71]	pixels	deep net	Caltech+ImageNet	ImageNet pre-training
AFS	[26]	multiple	linear SVM	INRIA	accelerated version of FeatSynth
AFS+Geo	[26]	multiple	linear SVM	INRIA	variant of AFS with geometry constraints
AR+PED	[8]	pixels	deep net	Caltech+ImageNet	ImageNet pre-training [source code]
CCF	[63]	deep	AdaBoost	Caltech	
CCF+CF	[63]	deep+channels	AdaBoost	Caltech	
Checkerboards	[68]	channels	AdaBoost	Caltech	
Checkerboards+	[68]	channels	AdaBoost	Caltech	Checkerboards + flow-based features from [47]
ChnFtrs	[19]	channels	AdaBoost	INRIA	updated (see addendum on author website)
CompACT-Deep	[9]	multiple	boosting	Caltech	
ConvNet	[51]	pixels	DeepNet	INRIA	
Crosstalk	[16]	channels	AdaBoost	INRIA	
DBN-Isol	[38]	HOG	DeepNet	INRIA	
DBN-Mut	[41]	HOG	DeepNet	INRIA/Caltech	
DeepCascade	[2]	pixels	DeepNet	Caltech	
DeepCascade+	[2]	pixels	DeepNet	Caltech+	uses Caltech+ETH+Daimler for training
DeepParts	[55]	pixels	DeepNet	Caltech	
FastCF	[14]	channels	AdaBoost	INRIA/Caltech	100 fps on a CPU
FasterRCNN+ATT	[70]	pixels	DeepNet	Caltech+	ImageNet data
F-DNN	[21]	pixels	DeepNet	Caltech+	ImageNet+ETH+TudBrussels data
F-DNN+SS	[21]	pixels	DeepNet	Caltech+	ImageNet+Cityscapes+ETH+TudBrussels data
F-DNN2+SS	[22]	pixels	DeepNet	Caltech+	ImageNet+Cityscapes+ETH+TudBrussels data
FeatSynth	[3]	multiple	linear SVM	INRIA	
FisherBoost	[52]	HOG+COV	FisherBoost	INRIA	
FPDW	[17]	channels	AdaBoost	INRIA	accelerated variant of ChnFtrs
FtrMine	[18]	channels	AdaBoost	INRIA	
Franken	[34]	channels	AdaBoost	INRIA	multiple occlusion specific models
GDFL	[29]	pixels	DeepNet	Caltech+	ImageNet data
HikSvm	[32]	HOG	HIK SVM	INRIA	boundary effect fixed since publication
HOG	[15]	HOG	linear SVM	INRIA	
HOG-LBP	[60]	HOG+LBP	linear SVM	INRIA	
InformedHaar	[67]	channels	AdaBoost	INRIA/Caltech	

		features	classifier	training	notes
JointDeep	[39]	color+gradient	deep net	INRIA/Caltech	
Katamari	[6]	channels	AdaBoost	INRIA/Caltech	combines methods [4, 20, 36, 40, 47]
LatSvm-V1	[23]	HOG	latent SVM	PASCAL	
LatSvm-V2	[24]	HOG	latent SVM	INRIA	
LDCF	[36]	channels	AdaBoost	Caltech	locally decorrelated channel features
LDCF++	[37]	channels	AdaBoost	Caltech	
LFOV	[1]	pixels	DeepNet	Caltech	
MLS	[35]	HOG	AdaBoost	INRIA	
MOCO	[11]	HOG+LBP	latent SVM	Caltech	
MRFC+Semantic	[13]	channels	boosting	Caltech+	CamVid+SiftFlow+KITTI data for segm.
MS-CNN	[10]	pixels	deep net	Caltech+ImageNet	ImageNet pre-training
MT-DPM	[62]	HOG	latent SVM	Caltech	
MT-DPM+Context	[62]	HOG	latent SVM	Caltech+	context obtained from a vehicle detector
MultiFtr	[61]	multiple	AdaBoost	INRIA	
MultiFtr+CSS	[58]	multiple	linear SVM	TUD-Motion	
MultiFtr+Motion	[58]	multiple	linear SVM	TUD-Motion	
MultiResC	[46]	HOG	latent SVM	Caltech	
MultiSDP	[65]	HOG+CSS	deep net	INRIA/Caltech	
NAMC	[56]	channels	AdaBoost	INRIA/Caltech	
pAUCBoost	[43]	HOG+COV	pAUCBoost	INRIA	optimized for low false-positives
PCN	[59]	pixels	deep net	Caltech+ImageNet	ImageNet pre-training
Pls	[50]	multiple	PLS+QDA	INRIA	
PoseInv	[30]	HOG	AdaBoost	INRIA+	trained with annotated silhouettes
PoseInvSvm	[30]	HOG	kernel SVM	INRIA+	trained with annotated silhouettes
RandForest	[33]	HOG+LBP	random forest	INRIA/Caltech	Caltech results include context (CGP)
Roerei	[5]	channels	AdaBoost	INRIA	
RPN+BF	[66]	pixels	DeepNet+AdaBoost	Caltech+ImageNet	ImageNet pre-training
SA-FastRCNN	[27]	pixels	deep net	Caltech+ImageNet	ImageNet pre-training
SCCPriors	[64]	channels	AdaBoost	INRIA/Caltech	
SCF+AlexNet	[25]	pixels	deep net	Caltech+ImageNet	ImageNet pre-training
SDN	[31]	pixels	deep net	INRIA/Caltech	
SDS-RCNN	[7]	pixels	deep net	Caltech+ImageNet	ImageNet pre-training
Shapelet	[49]	gradients	AdaBoost	INRIA	with boundary effects fixed [61]
Shapelet-orig	[49]	gradients	AdaBoost	INRIA	original implementation
ShearFtrs	[48]	channels	AdaBoost	Caltech	features based on shearlet transform
SketchTokens	[28]	channels	AdaBoost	INRIA+	Sketch Tokens were trained on BSDS
SpatialPooling	[44]	multiple	pAUCBoost	INRIA/Caltech	spatial pooling + shrinkage to avoid overfitting
SpatialPooling+	[45]	multiple	pAUCBoost	Caltech	improved version of [43, 44] + flow features
TLL-TFA	[53]	pixels	deep net	Caltech+	ImageNet+CityPersons data
TA-CNN	[54]	pixels	DeepNet	Caltech++	augmented with external data
UDN+	[42]	pixels	deep net	Caltech+ImageNet	ImageNet pre-training
VeryFast	[4]	channels	AdaBoost	INRIA	
VJ	[57]	Haar	AdaBoost	INRIA	implementation from [61]
VJ-OpenCV	[57]	Haar	AdaBoost	INRIA	implementation from OpenCV
WordChannels	[12]	WordChannels	AdaBoost	INRIA/Caltech	
***+2Ped**	[40]	HOG	latent SVM	INRIA+	adds 2-person detector as context

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