Caltech Pedestrian Dataset: Evaluated Algorithms

		features	classifier	training	notes
ACF	[17]	channels	AdaBoost	INRIA	evolution of ChnFtrs [source code]
ACF-Caltech	[17]	channels	AdaBoost	Caltech	evolution of ChnFtrs [source code]
ACF-Caltech+	[30]	channels	AdaBoost	Caltech	uses deeper trees and denser sampling
ACF+SDt	[39]	channels	AdaBoost	Caltech	SDt = Stabilized Dt (motion features)
AFS	[21]	multiple	linear SVM	INRIA	accelerated version of FeatSynth
AFS+Geo	[21]	multiple	linear SVM	INRIA	variant of AFS with geometry constraints
CCF	[52]	deep	AdaBoost	Caltech	
CCF+CF	[52]	deep+channels	AdaBoost	Caltech	
Checkerboards	[57]	channels	AdaBoost	Caltech	
Checkerboards+	[57]	channels	AdaBoost	Caltech	Checkerboards + flow-based features from [39]
ChnFtrs	[16]	channels	AdaBoost	INRIA	updated (see addendum on author website)
CompACT-Deep	[7]	multiple	boosting	Caltech	
ConvNet	[42]	pixels	DeepNet	INRIA	
Crosstalk	[13]	channels	AdaBoost	INRIA	
DBN-Isol	[31]	HOG	DeepNet	INRIA	
DBN-Mut	[34]	HOG	DeepNet	INRIA/Caltech	
DeepCascade	[2]	pixels	DeepNet	Caltech	
DeepCascade+	[2]	pixels	DeepNet	Caltech+	uses Caltech+ETH+Daimler for training
DeepParts	[45]	pixels	DeepNet	Caltech	
FastCF	[11]	channels	AdaBoost	INRIA/Caltech	100 fps on a CPU
FeatSynth	[3]	multiple	linear SVM	INRIA	
FisherBoost	[43]	HOG+COV	FisherBoost	INRIA	
FPDW	[14]	channels	AdaBoost	INRIA	accelerated variant of ChnFtrs
FtrMine	[15]	channels	AdaBoost	INRIA	
Franken	[28]	channels	AdaBoost	INRIA	multiple occlusion specific models
HikSvm	[26]	HOG	HIK SVM	INRIA	boundary effect fixed since publication
HOG	[12]	HOG	linear SVM	INRIA	
HOG-LBP	[49]	HOG+LBP	linear SVM	INRIA	
InformedHaar	[56]	channels	AdaBoost	INRIA/Caltech	
JointDeep	[32]	color+gradient	deep net	INRIA/Caltech	
Katamari	[6]	channels	AdaBoost	INRIA/Caltech	combines methods [4, 17, 30, 33, 39]
LatSvm-V1	[18]	HOG	latent SVM	PASCAL	
LatSvm-V2	[19]	HOG	latent SVM	INRIA	
LDCF	[30]	channels	AdaBoost	Caltech	locally decorrelated channel features
LFOV	[1]	pixels	DeepNet	Caltech	
MLS	[29]	HOG	AdaBoost	INRIA	
MOCO	[9]	HOG+LBP	latent SVM	Caltech	
MS-CNN	[8]	pixels	deep net	Caltech+ImageNet	ImageNet pre-training
MT-DPM	[51]	HOG	latent SVM	Caltech	
MT-DPM+Context	[51]	HOG	latent SVM	Caltech+	context obtained from a vehicle detector

		features	classifier	training	notes
MultiFtr	[50]	multiple	AdaBoost	INRIA	
MultiFtr+CSS	[48]	multiple	linear SVM	TUD-Motion	
MultiFtr+Motion	[48]	multiple	linear SVM	TUD-Motion	
MultiResC	[38]	HOG	latent SVM	Caltech	
MultiSDP	[54]	HOG+CSS	deep net	INRIA/Caltech	
NAMC	[46]	channels	AdaBoost	INRIA/Caltech	
pAUCBoost	[35]	HOG+COV	pAUCBoost	INRIA	optimized for low false-positives
Pls	[41]	multiple	PLS+QDA	INRIA	
PoseInv	[24]	HOG	AdaBoost	INRIA+	trained with annotated silhouettes
PoseInvSvm	[24]	HOG	kernel SVM	INRIA+	trained with annotated silhouettes
RandForest	[27]	HOG+LBP	random forest	INRIA/Caltech	Caltech results include context (CGP)
Roerei	[5]	channels	AdaBoost	INRIA	
RPN+BF	[55]	pixels	DeepNet+AdaBoost	Caltech+ImageNet	ImageNet pre-training
SA-FastRCNN	[22]	pixels	deep net	Caltech+ImageNet	ImageNet pre-training
SCCPriors	[53]	channels	AdaBoost	INRIA/Caltech	
SCF+AlexNet	[20]	pixels	deep net	Caltech+ImageNet	ImageNet pre-training
SDN	[25]	pixels	deep net	INRIA/Caltech	
Shapelet	[40]	gradients	AdaBoost	INRIA	with boundary effects fixed [50]
Shapelet-orig	[40]	gradients	AdaBoost	INRIA	original implementation
SketchTokens	[23]	channels	AdaBoost	INRIA+	Sketch Tokens were trained on BSDS
SpatialPooling	[36]	multiple	pAUCBoost	INRIA/Caltech	spatial pooling + shrinkage to avoid overfitting
SpatialPooling+	[37]	multiple	pAUCBoost	Caltech	improved version of [35, 36] + flow features
TA-CNN	[44]	pixels	DeepNet	Caltech++	augmented with external data
VeryFast	[4]	channels	AdaBoost	INRIA	
VJ	[47]	Haar	AdaBoost	INRIA	implementation from [50]
VJ-OpenCV	[47]	Haar	AdaBoost	INRIA	implementation from OpenCV
WordChannels	[10]	WordChannels	AdaBoost	INRIA/Caltech	
***+2Ped**	[33]	HOG	latent SVM	INRIA+	adds 2-person detector as context

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