## Caltech Pedestrian Dataset:
### Evaluated Algorithms

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<th>Algorithm</th>
<th>features</th>
<th>classifier</th>
<th>training</th>
<th>notes</th>
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</thead>
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<td>ACF</td>
<td>[19] channels</td>
<td>AdaBoost</td>
<td>INRIA</td>
<td>evolution of ChnFtrs [source code]</td>
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<td>ACF++</td>
<td>[34] channels</td>
<td>AdaBoost</td>
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<td>ACF-Caltech</td>
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<td>evolution of ChnFtrs [source code]</td>
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<td>ACF-Caltech+</td>
<td>[33] channels</td>
<td>AdaBoost</td>
<td>Caltech</td>
<td>uses deeper trees and denser sampling</td>
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<td>ACF+SDt</td>
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<td>Caltech</td>
<td>SDt = Stabilized Dt (motion features)</td>
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<td>AFS+Geo</td>
<td>[24] multiple linear SVM</td>
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<td>variant of AFS with geometry constraints</td>
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<td>CCF</td>
<td>[58] deep</td>
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<td>CCF+CF</td>
<td>[58] deep + channels</td>
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<td>Checkerboards</td>
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<td>Checkerboards+</td>
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<td>Checkerboards + flow-based features from [44]</td>
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<td>ChnFtrs</td>
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<td>updated (see addendum on author website)</td>
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<td>CompACT-Deep</td>
<td>[8] multiple boosting</td>
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<td>100 fps on a CPU</td>
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<td>HikSvm</td>
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<td>InformedHaar</td>
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<td>combines methods [4, 19, 33, 37, 44]</td>
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<td>Caltech results include context (CGP)</td>
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<td>with boundary effects fixed</td>
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<td>original implementation</td>
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<td>WordChannels</td>
<td>AdaBoost</td>
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<td>*+2Ped</td>
<td>HOG</td>
<td>latent SVM</td>
<td>INRIA+</td>
<td>adds 2-person detector as context</td>
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</table>

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