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static obstacle collisions. The comparison showed that even with a small sample size, the split training outperforms the all-sample-based one. Moreover, it was observed that, within the weighted ensemble methods, the individual DNN models contributed with more accurate predictions than the CNNs. We expect that, with more samples, the DNNs could be reliably used for the recognition, with the CNNs supporting classification. However, based on the binary classification CNN created in addition, the CNNs should not be used for the recognition of danger, but only for discriminating between static and dynamic obstacles which are about to collide with the robot. This approach may mean that less data is required for training danger recognition, as the proposed DNNs, unlike the image-based models, did not require a large dataset to achieve a reasonable danger recognition accuracy.

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