precision begins to slightly yield from r=3. We can conclude that there is a really clear improvement of the results by using the DFFNN, this improvement is more sensitive on this database with regard to the first one.

From our two-step experiments, we have been able to show the superiority of the DFFNNs compared to the graph-based methods used in this context. Among the strong points, too, of our conduct is that the construction of such a model is very feasible also in a massive data context.

Table 8. Average accuracy (second database)

Second database	R = 1	R = 2	R = 3
KNN	-	90,58	-
LLE	-	95	-
TPWRLS	-	97,33	-
DFFNN	99,805	99,965	99,495

5. CONCLUSIONS

We have evaluated the DFFNN for the objects categorization with the cross-validation scheme that is commonly used in the domain of pattern recognition. Objects can be captured by either a surveillance camera or an onboard camera. In this work, we have presented a quantitative evaluation using the DFFNN and some graph-based methods schemes, applied, firstly to outdoor object categorization using a first public outdoor image dataset, and secondly, to object categorization using a second public dataset. From our two-step experiments, we have been able to show the superiority of the DFFNNs compared to the graph-based methods used in this context. Among the strong points, too, of our conduct is that the construction of such a model is very feasible also in a massive data context. It is in our perspective for future research to test this architecture with other LBP neighborhood types on a real data captured directly from a surveillance camera or an onboard camera.

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