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5 Conclusion

In this work we propose the Bloom WiSARD model which extends WiSARD by implementing RAM nodes as Bloom filters. By using Bloom filters, memory resources are significantly reduced and for pattern recognition purposes we experimentally found that Bloom filters can build robustness into the system. Our experiments show that the model provides good accuracy and requires low training and testing times. In addition, it consumes up to 6 orders of magnitude less resources than standard WiSARD and about 7.7 times less resources than WiSARD implemented with dictionaries. Future work will focus on extending Bloom filter operations such as frequency counts of elements stored, in order to enable Bloom WiSARD to use improved techniques such as DRASiW [13] or the Bloom filter false free zone [14]. More broadly, we envision that this work is one step further towards the use of Bloom filters for machine learning [4, 15].

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