One Size Does Not Fit All: Multi-Scale, Cascaded RNNs for Radar Classification

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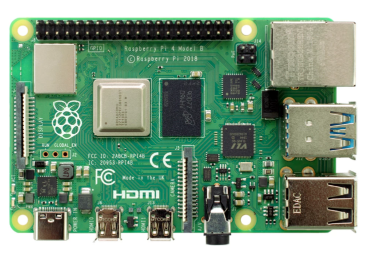
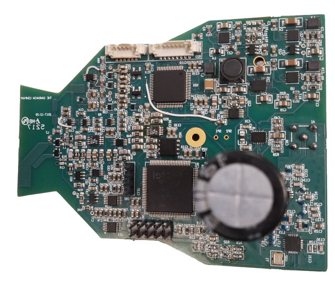
1. IoT Requirements in The Smart City

- Resource efficiency

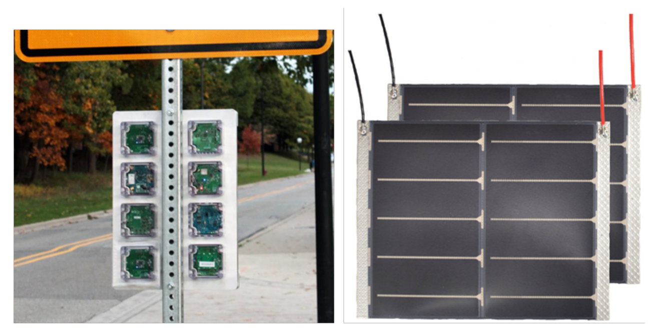


vs.

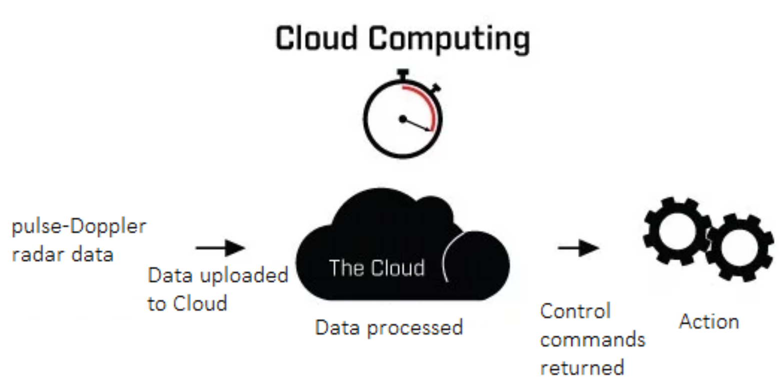


- Deployment feasibility

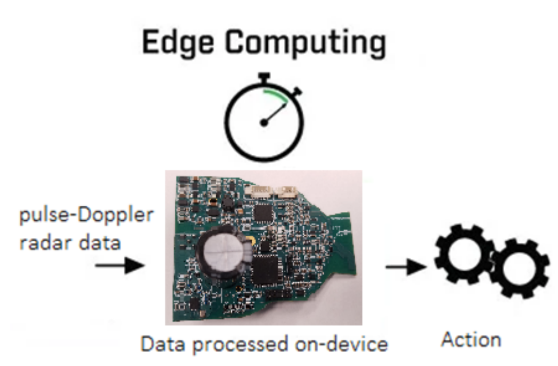
vs.



- Privacy preserving



vs.



2. N+1-class Radar Classification

- Example of N source classes + clutter class (N+1-class) classification

Class: Clutter

Class: Human

Class: Scooter

- Efficiency-Accuracy trade-off in existing solutions

ML Model	Accuracy	FLOPS	Fits on Cortex-M3?
SVM (15 features)	0.85	37K	Yes
LSTM	0.89	100K	No
CNN (1s FFT)	0.91	1.3M	No
EMI-LSTM	0.90	20K	No
EMI-FastGRNN	0.88	8K	Yes

- Interesting events may occur rarely

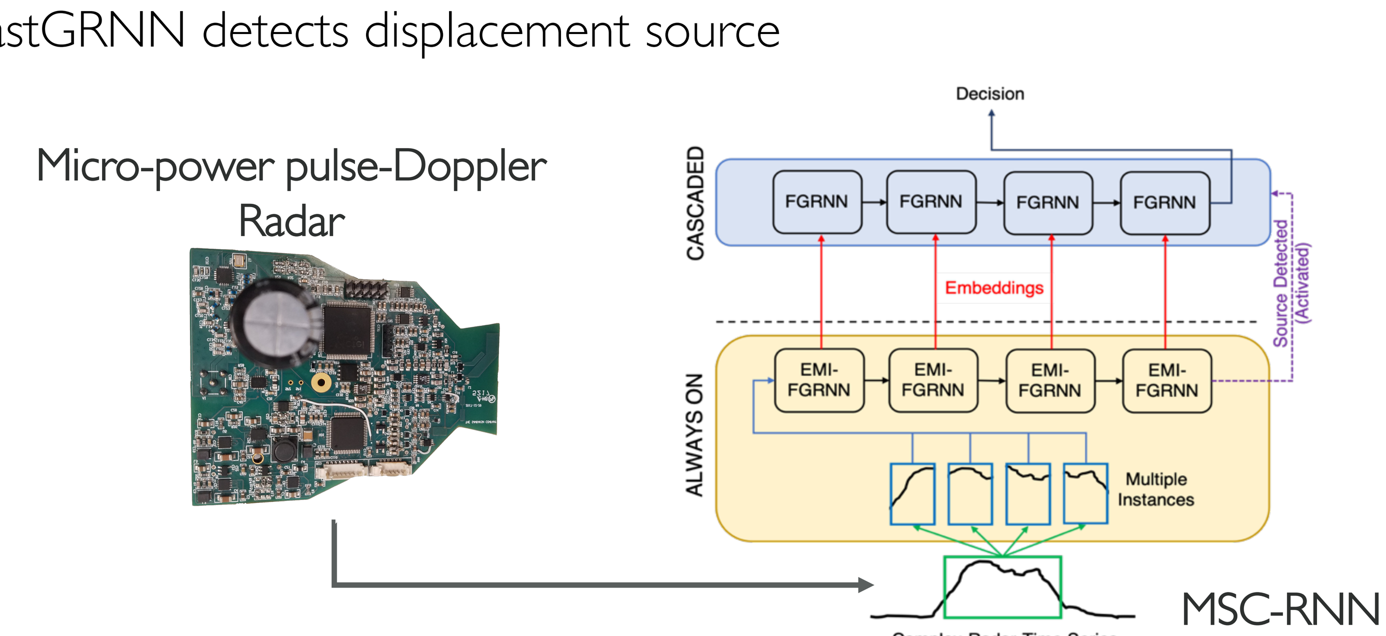
3. MSC-RNN Solution for N+1classes

- Multi-Scale Cascaded RNN (MSC-RNN) handles the two sub-problems of clutter rejection and source discrimination at different time scales of featurization
- MSC-RNN Components:

(i) EMI-FastGRNN: works at instance-level and is continuously active

(ii) FastGRNN: works at window-level

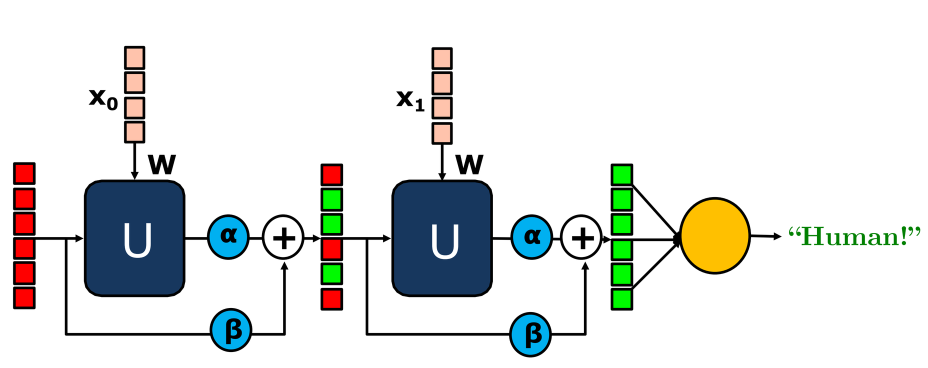
Both the components are cascaded so that FastGRNN is invoked only when EMI-FastGRNN detects displacement source



- Fast(G)RNN

- FastRNN stabilizes training with residual connections and adds just 2 additional scalars, α & β

- α & β when converted to vector gates result in FastGRNN



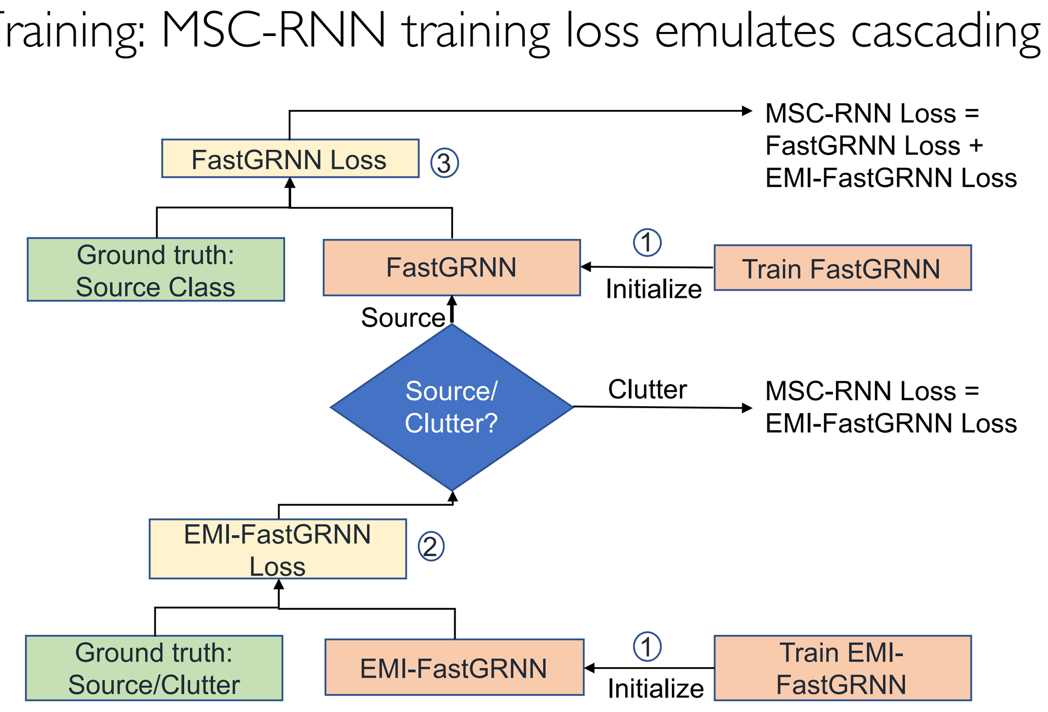
FastRNN

$$\tilde{h}_t = \sigma(\mathbf{W}\mathbf{x}_t + \mathbf{U}\mathbf{h}_{t-1} + \mathbf{b})$$
$$\mathbf{h}_t = \alpha\,\tilde{\mathbf{h}}_t + \beta\,\mathbf{h}_{t-1}$$

FastGRNN

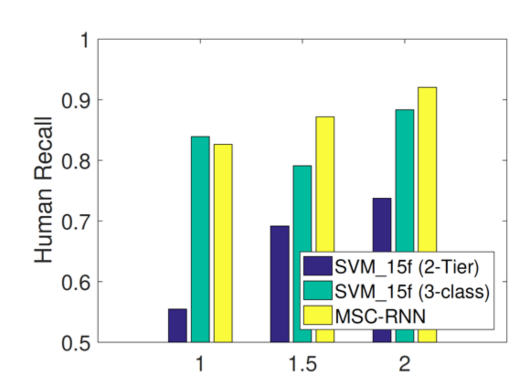
$$\mathbf{z}_t = \sigma(\mathbf{W}\mathbf{x}_t + \mathbf{U}\mathbf{h}_{t-1} + \mathbf{b}_z)$$
$$\tilde{\mathbf{h}}_t = \tanh(\mathbf{W}\mathbf{x}_t + \mathbf{U}\mathbf{h}_{t-1} + \mathbf{b}_h)$$
$$\mathbf{h}_t = (\zeta(1-\mathbf{z}_t)+\nu) \odot \tilde{\mathbf{h}}_t + \mathbf{z}_t \odot \mathbf{h}_{t-1}$$

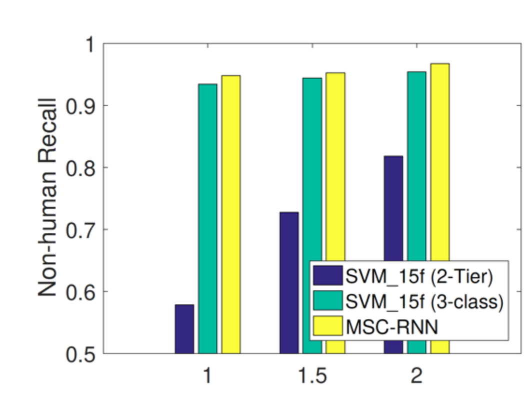
- MSC-RNN Training: MSC-RNN training loss emulates cascading behavior



4. Performance of MSC-RNN

- Performance comparison with SVM: Outperforms all-domain feature handcrafting at mote scale with purely time-domain feature learning



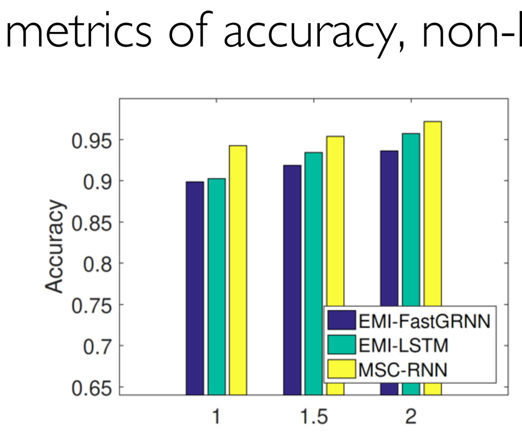


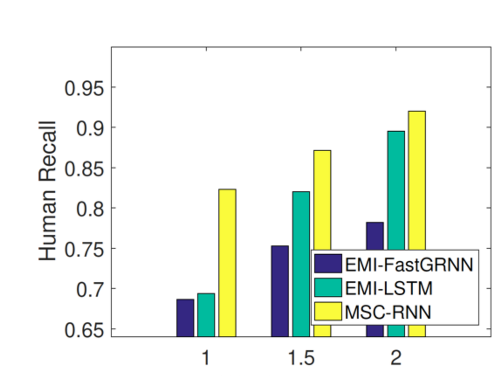
Win. Len. (s)	Accuracy		Clutter Recall	
	SVM_15f (3-class)	MSC-RNN	SVM_15f (3-class)	MSC-RNN
1	0.851	0.944	0.758	0.999
1.5	0.934	0.954	0.996	0.999
2	0.959	0.972	0.999	1.000

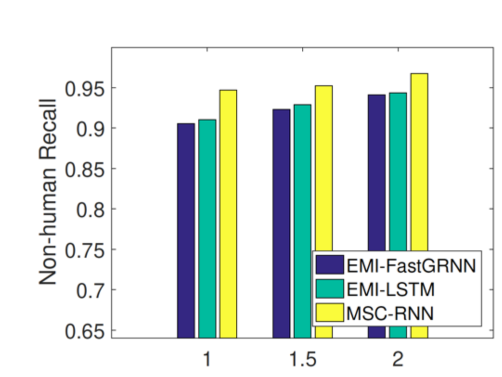
- Feature computation comparison with SVM: 3.5x more efficient than a competitive SVM solution

Architecture	Est. Duty Cycle (Cortex-M3)	
	97% Clutter	98% Clutter
MSC-RNN (Inp. dim.=2)	21.00%	20.00%
MSC-RNN (Inp. dim.=16)	10.87%	10.70%
2-Tier SVM	2.05%	1.70%
3-Class SVM	35.00%	35.00%

- Comparison with EMI: Outperforms monolithic EMI algorithms on all three metrics of accuracy, non-human and human recalls







5. References

[1] *Roy, Dhrubojyoti, et al. One size does not fit all: Multi-scale, cascaded RNNs for radar classification. In ACM BuildSys 2019*

[2] *Kusupati, Aditya, et al. Fastgrnn: A fast, accurate, stable and tiny kilobyte sized gated recurrent neural network. In NeurIPS 2018*

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