手把手智能品檢與預知維修實務

結合影像分析與時頻域分析的模型架構

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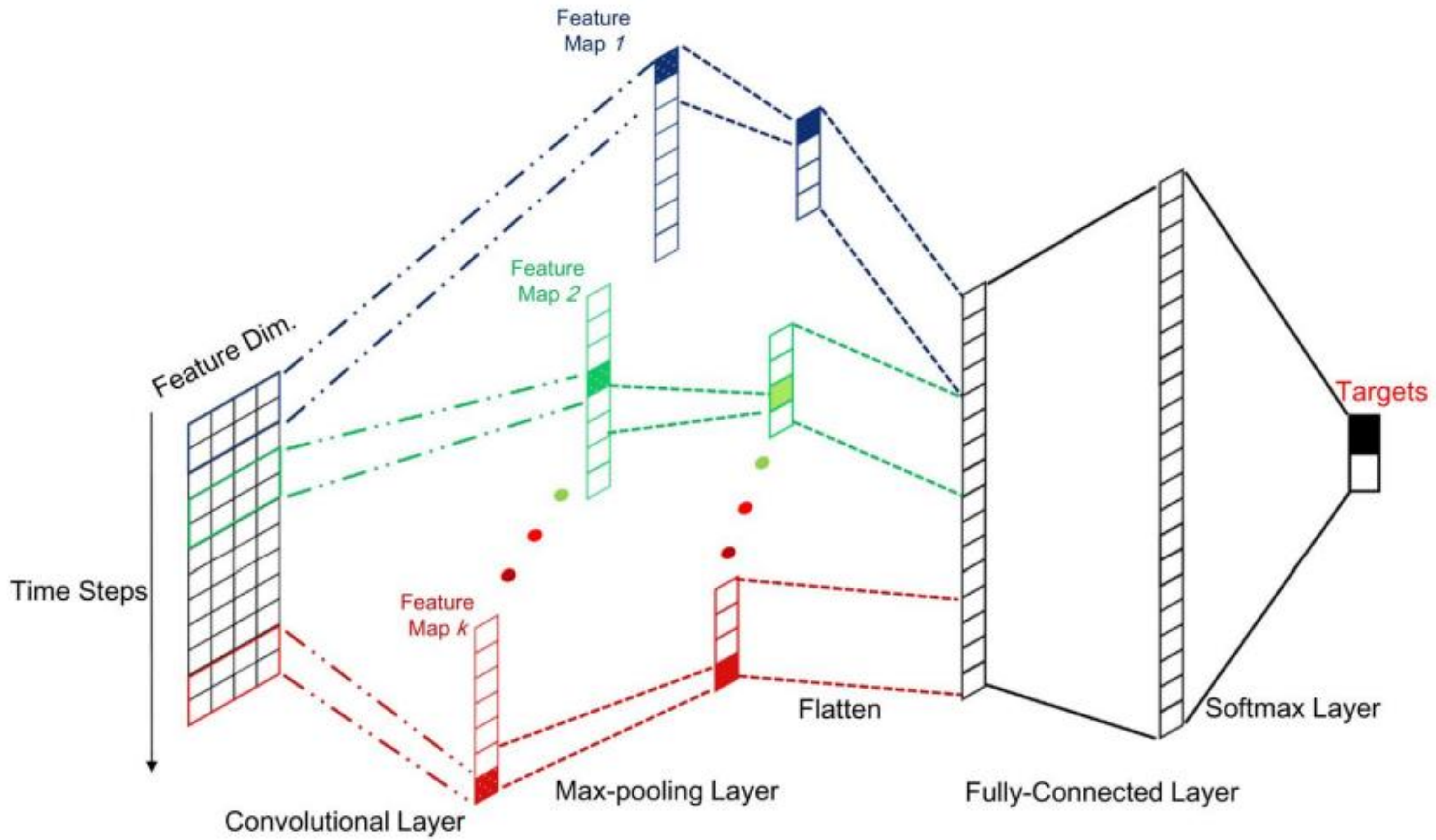
摘要

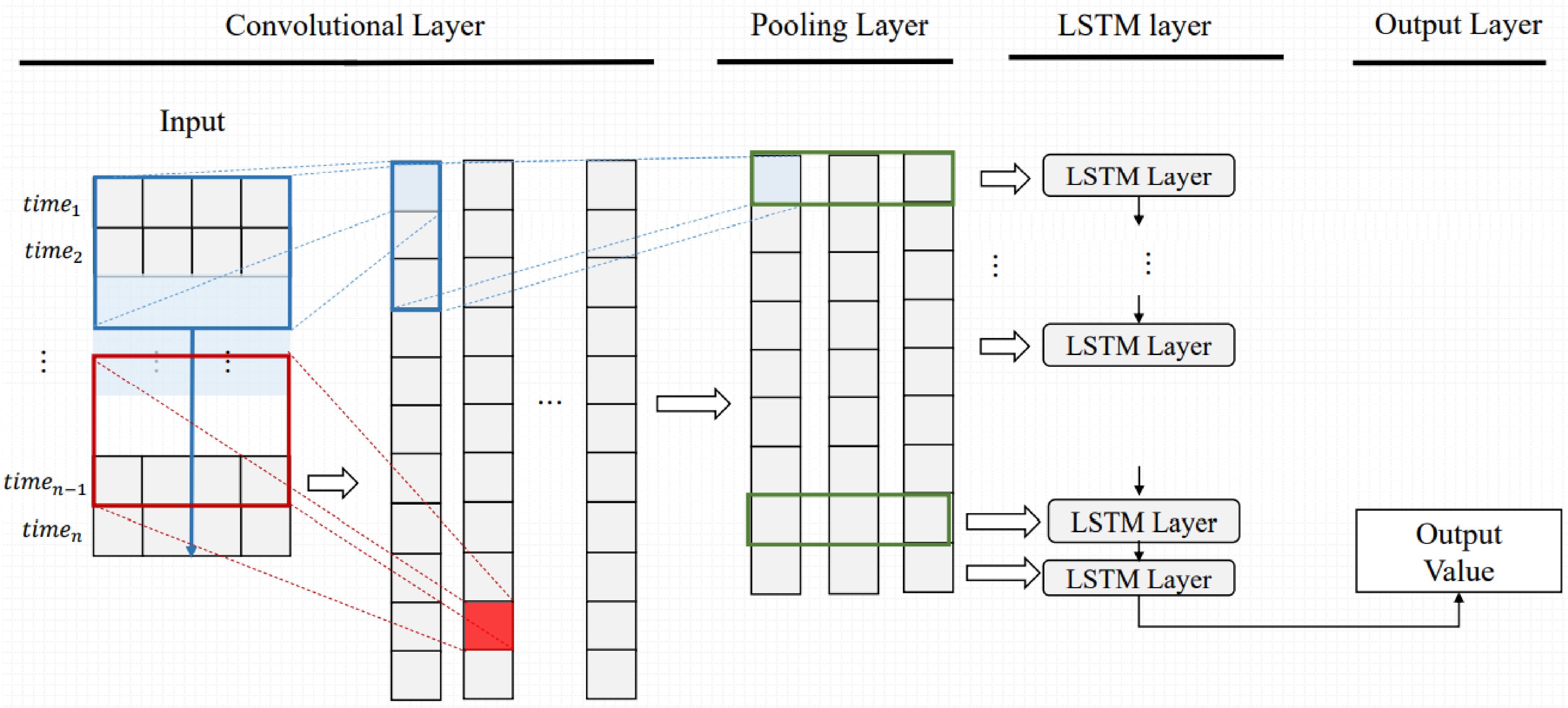
- One-Dimensional CNN (1DCNN)
- 1DCNN-LSTM
- Temporal Convolution Networks (TCN)
- TCN-LSTM

One-Dimensional CNN (1DCNN)



Zhao, R., Yan, R., Chen, Z., Mao, K., Wang, P., & Gao, R. X. (2019). Deep learning and its applications to machine health monitoring. Mechanical Systems and Signal Processing, 115, 213-237.(大陸西安交大, 新加坡南洋理工, 美國凱斯西儲, sitation:513)

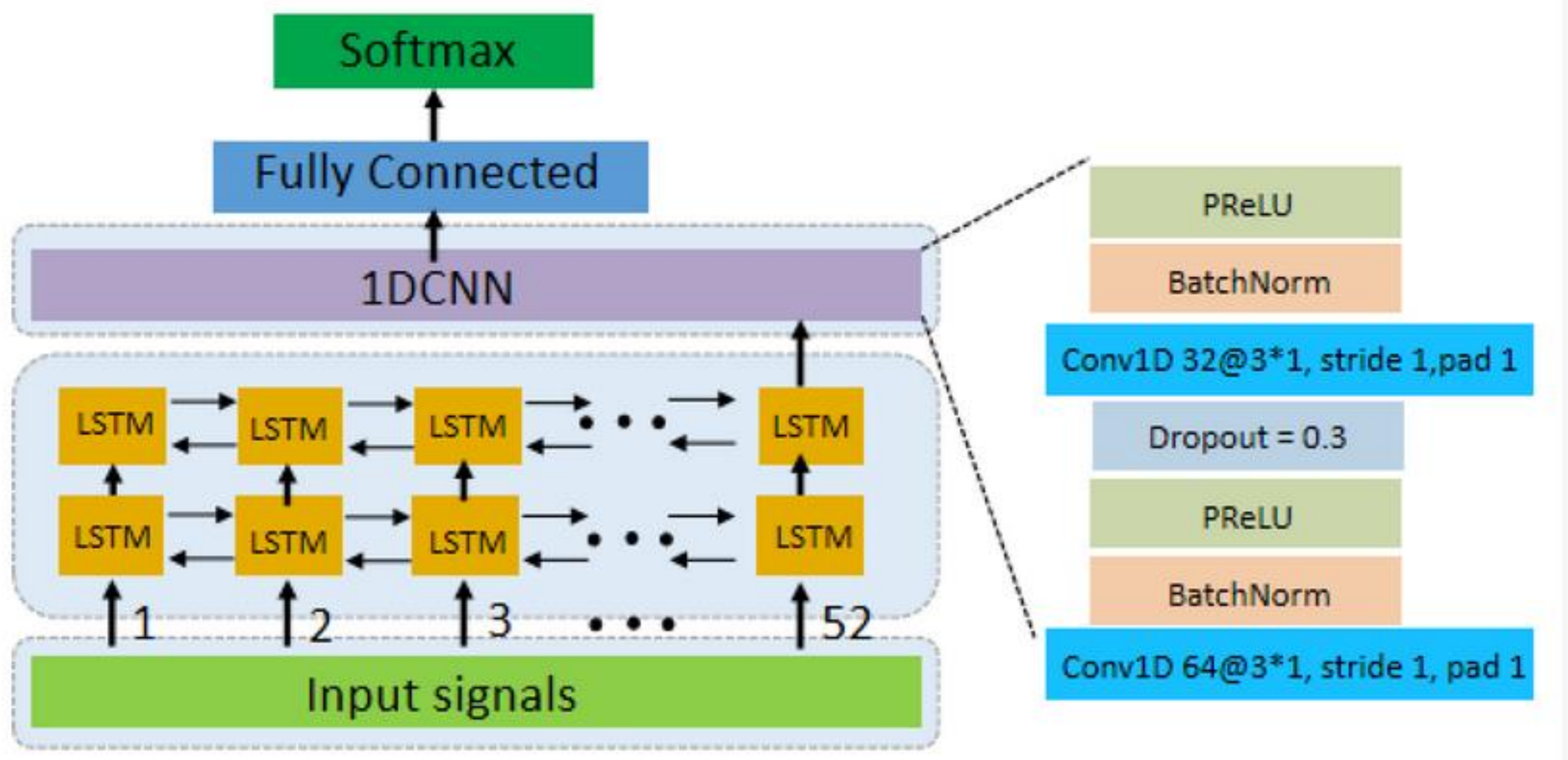
1DCNN-LSTM



Convolutional Layer
Pooling Layer
LSTM layer
Output Layer
Input
$time_1$
$time_2$
$time_{n-1}$
$time_n$
LSTM Layer
LSTM Layer
LSTM Layer
LSTM Layer
Output Value

1DCNN-LSTM v.s. LSTM-1DCNN

Figure 2. LCNN Architecture diagram, the LCNN consists of 2 LSTM layers, 2 one-dimensional convolution layers and 1 output layer. We use 2 LSTM layers, and each LSTM layer has 52 cells, and every cell has 64 hidden layers.



Chen, Lin, et al. “Hand gesture recognition using compact CNN via surface electromyography signals.” *Sensors* 20.3 (2020): 672

CNN-LSTM v.s. LSTM-CNN

Figure 8. The gesture categories in the Exercise A dataset.

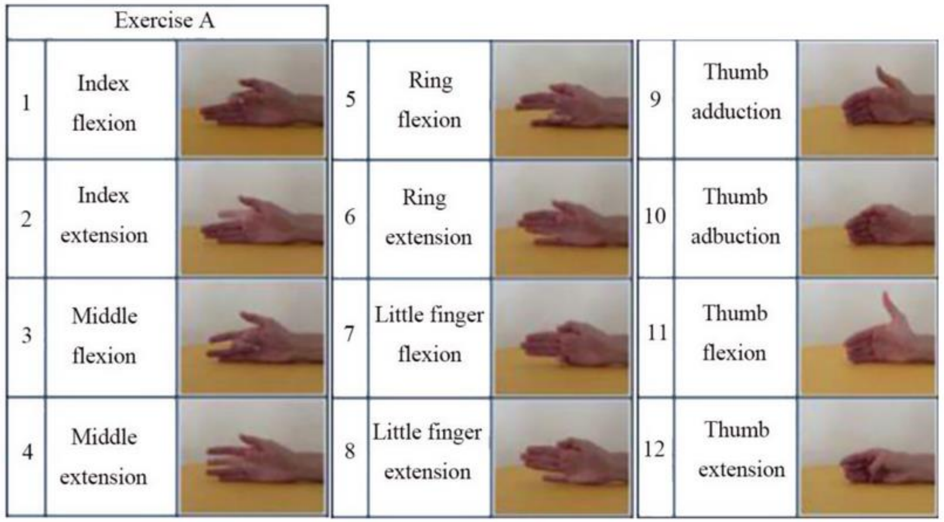
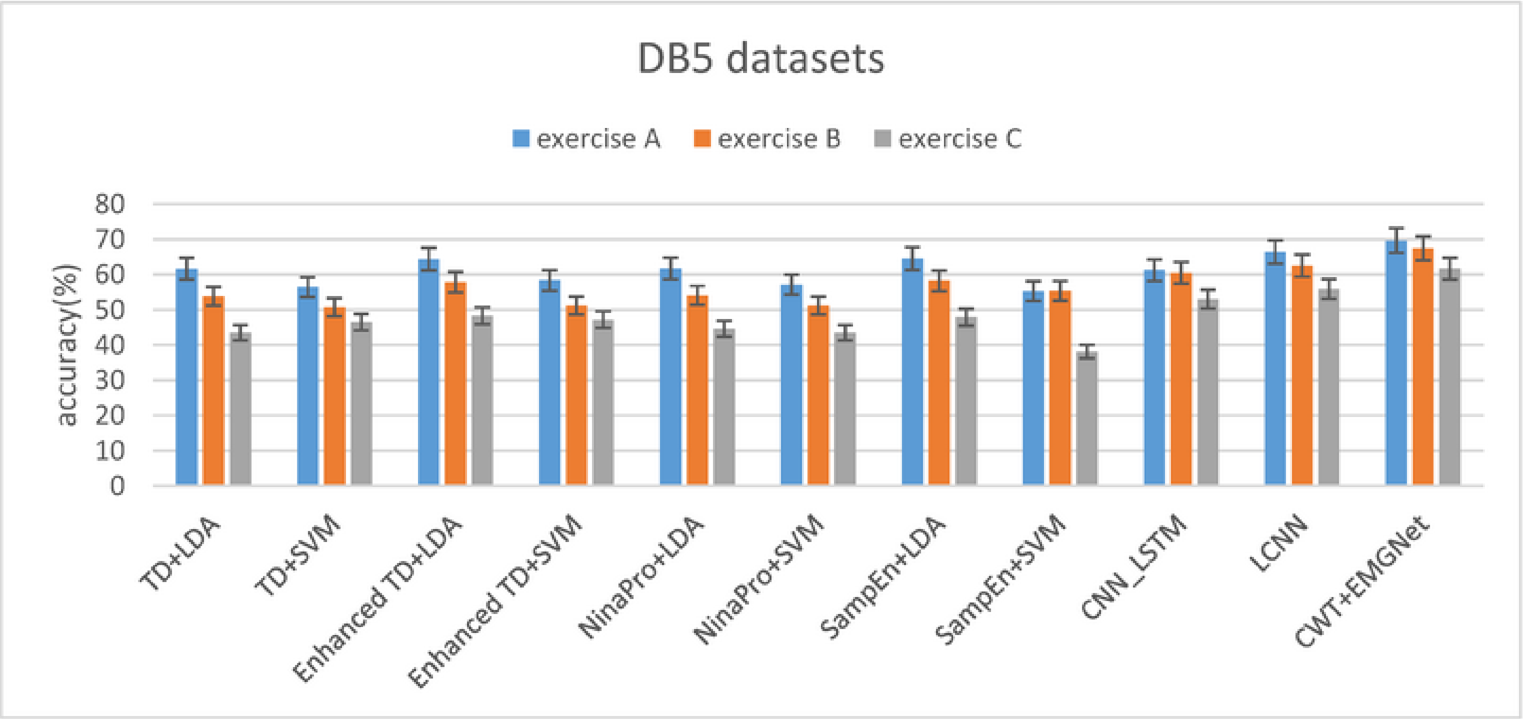


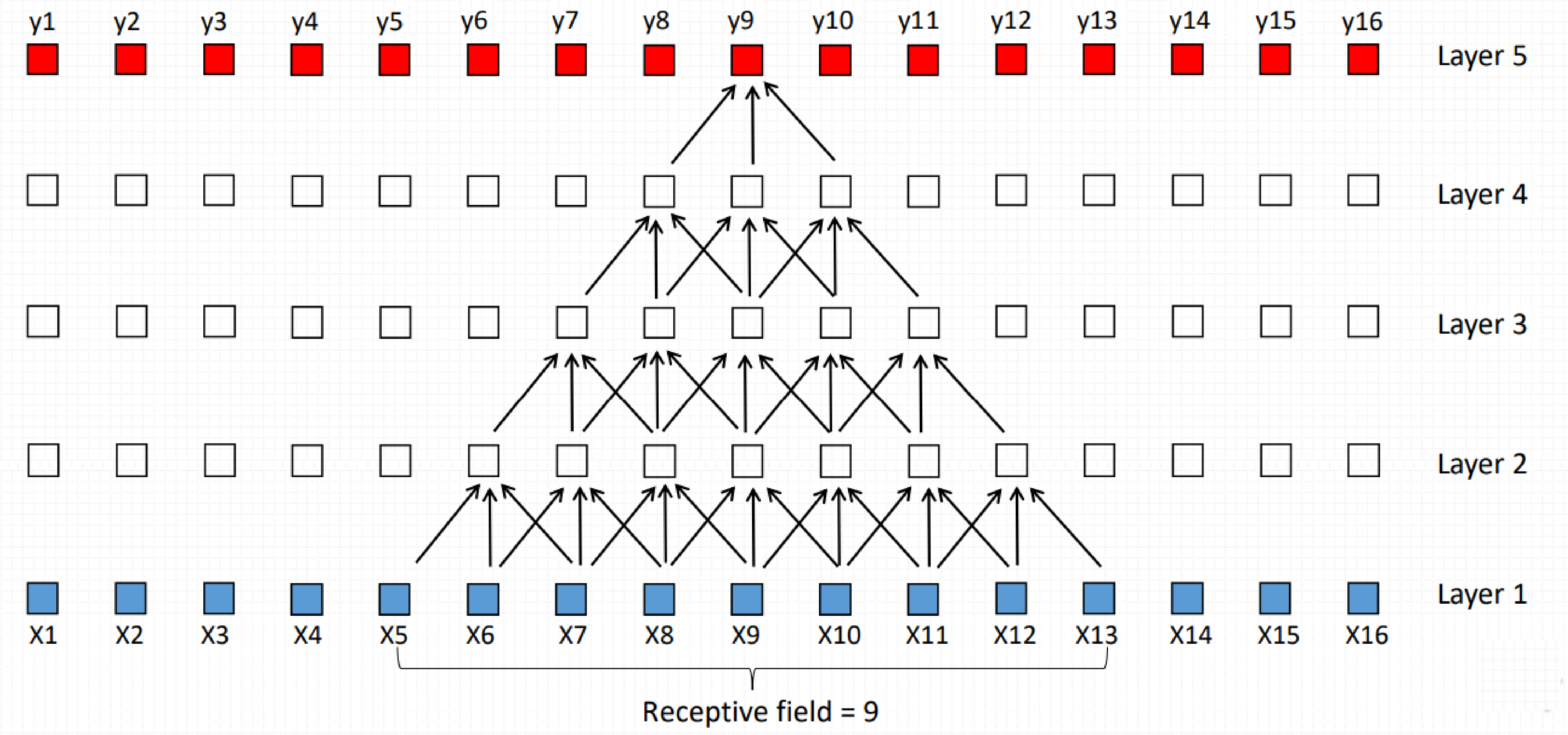
Figure 11. The average accuracy of three subsets on the DB5 Dataset.



Chen, Lin, et al. "Hand gesture recognition using compact CNN via surface electromyography signals." *Sensors* 20.3 (2020): 672

Temporal Convolution Networks (TCN)

(general Convolution Networks)



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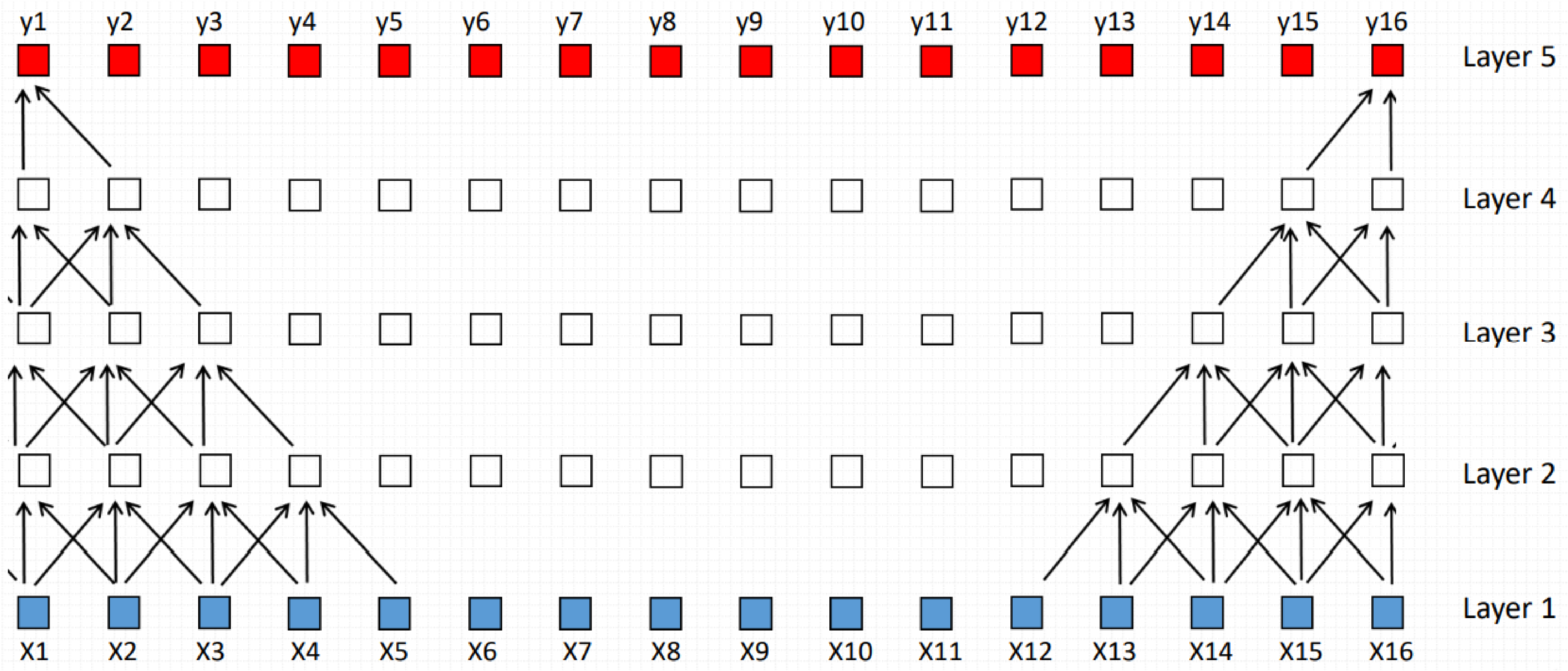
Temporal Convolution Networks (TCN)

(general Convolution Networks)



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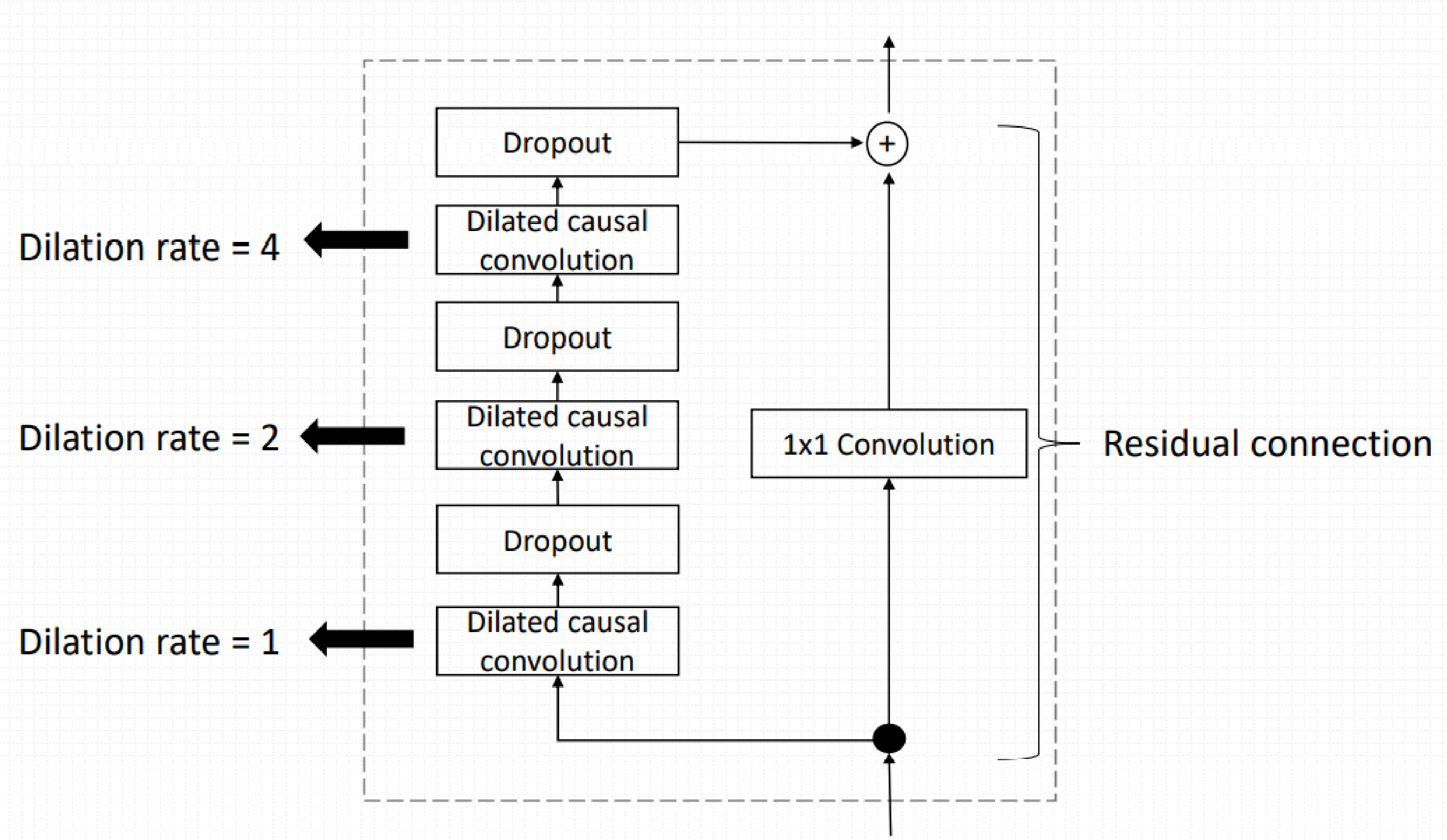
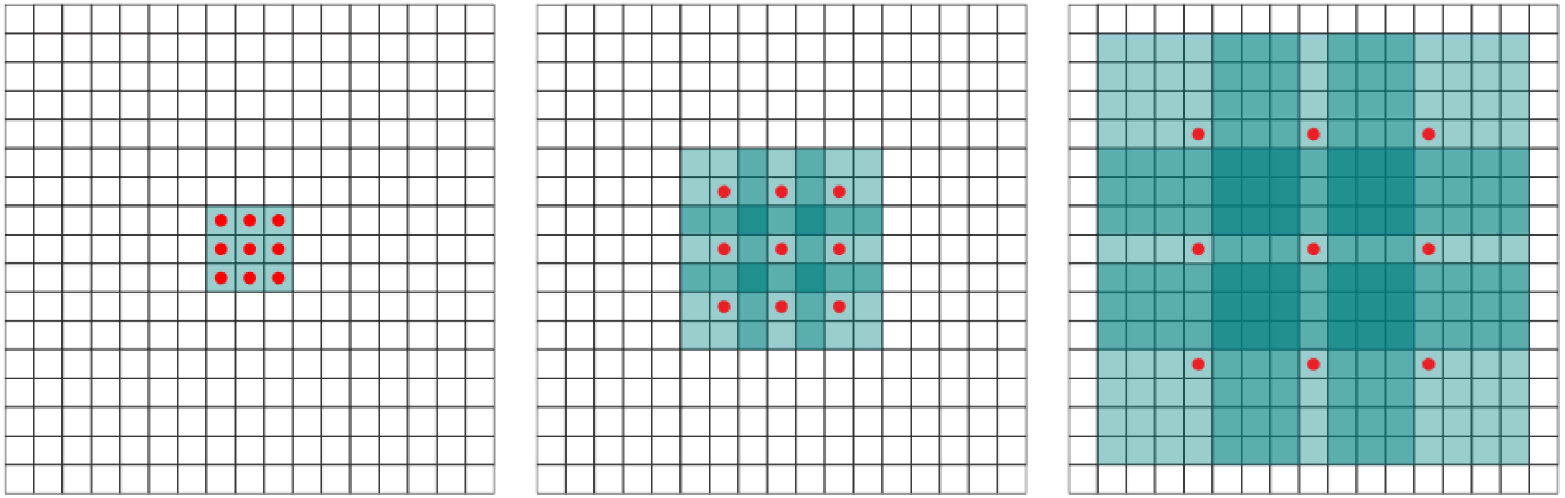
Temporal Convolution Networks (TCN)



Bai, Shaojie, J. Zico Kolter, and Vladlen Koltun. "An empirical evaluation of generic convolutional and recurrent networks for sequence modeling." *arXiv preprint arXiv:1803.01271* (2018).

Temporal Convolution Networks (TCN)

(Dilation Convolution)



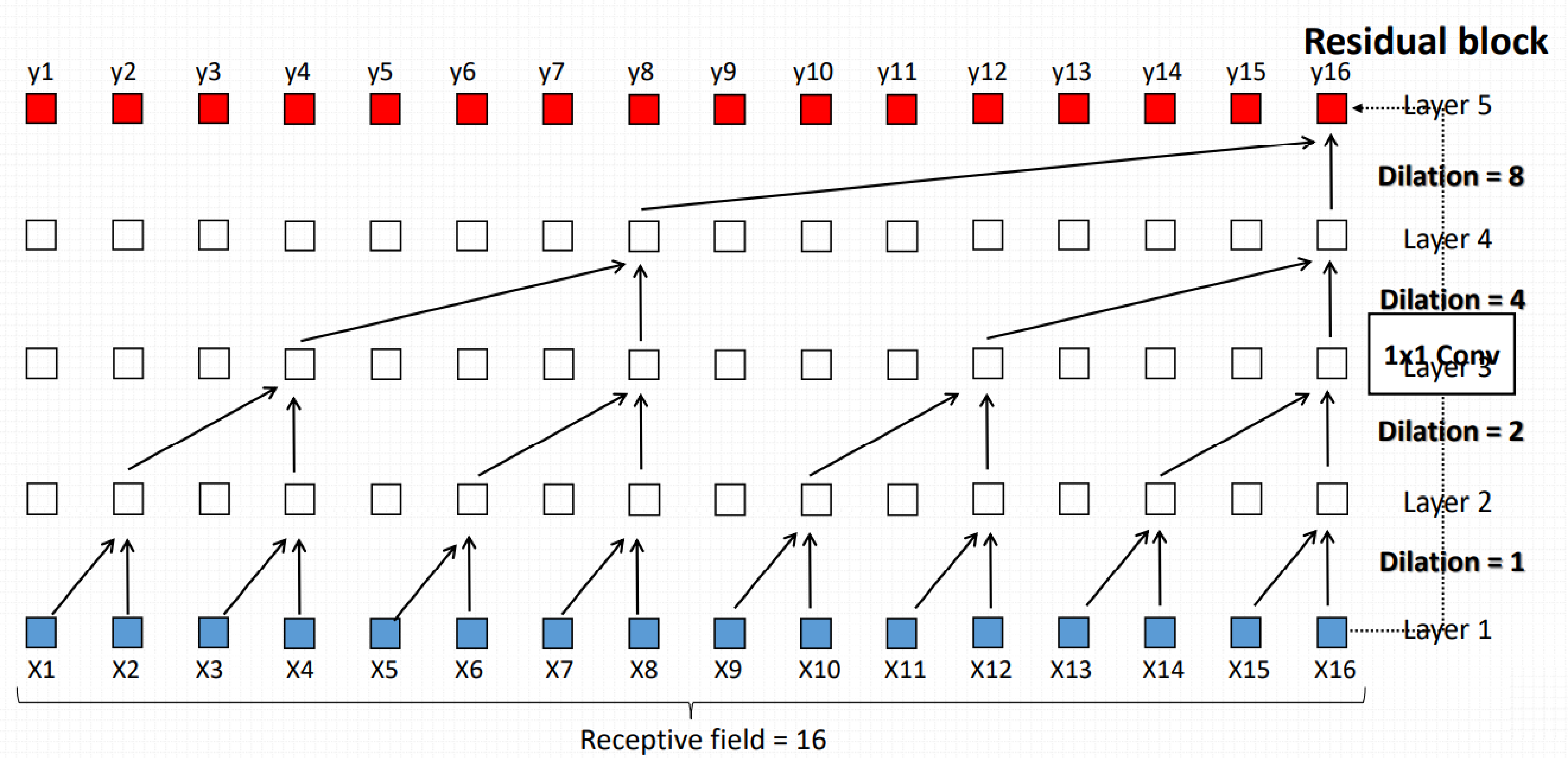
(a) (b) (c)

Figure 1: Systematic dilation supports exponential expansion of the receptive field without loss of resolution or coverage. (a) F_1 is produced from F_0 by a 1-dilated convolution; each element in F_1 has a receptive field of 3×3. (b) F_2 is produced from F_1 by a 2-dilated convolution; each element in F_2 has a receptive field of 7×7. (c) F_3 is produced from F_2 by a 4-dilated convolution; each element in F_3 has a receptive field of 15×15. The number of parameters associated with each layer is identical. The receptive field grows exponentially while the number of parameters grows linearly.

Yu, Fisher, and Vladlen Koltun. "Multi-scale context aggregation by dilated convolutions." *arXiv preprint arXiv:1511.07122* (2015).(Princeton University, sitation:3720)

Temporal Convolution Networks (TCN)

(Dilation-causal convolution & Residual connection)



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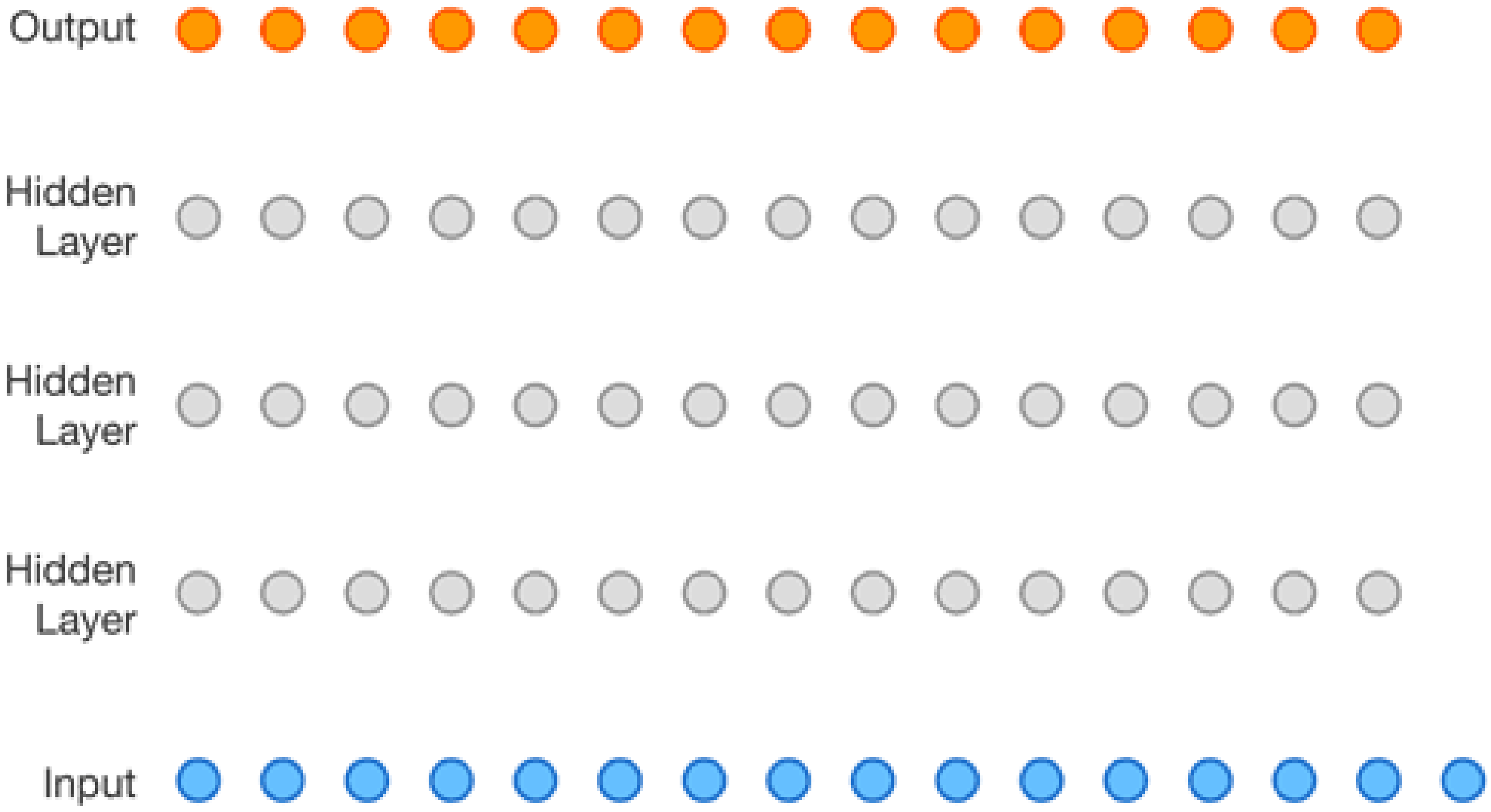
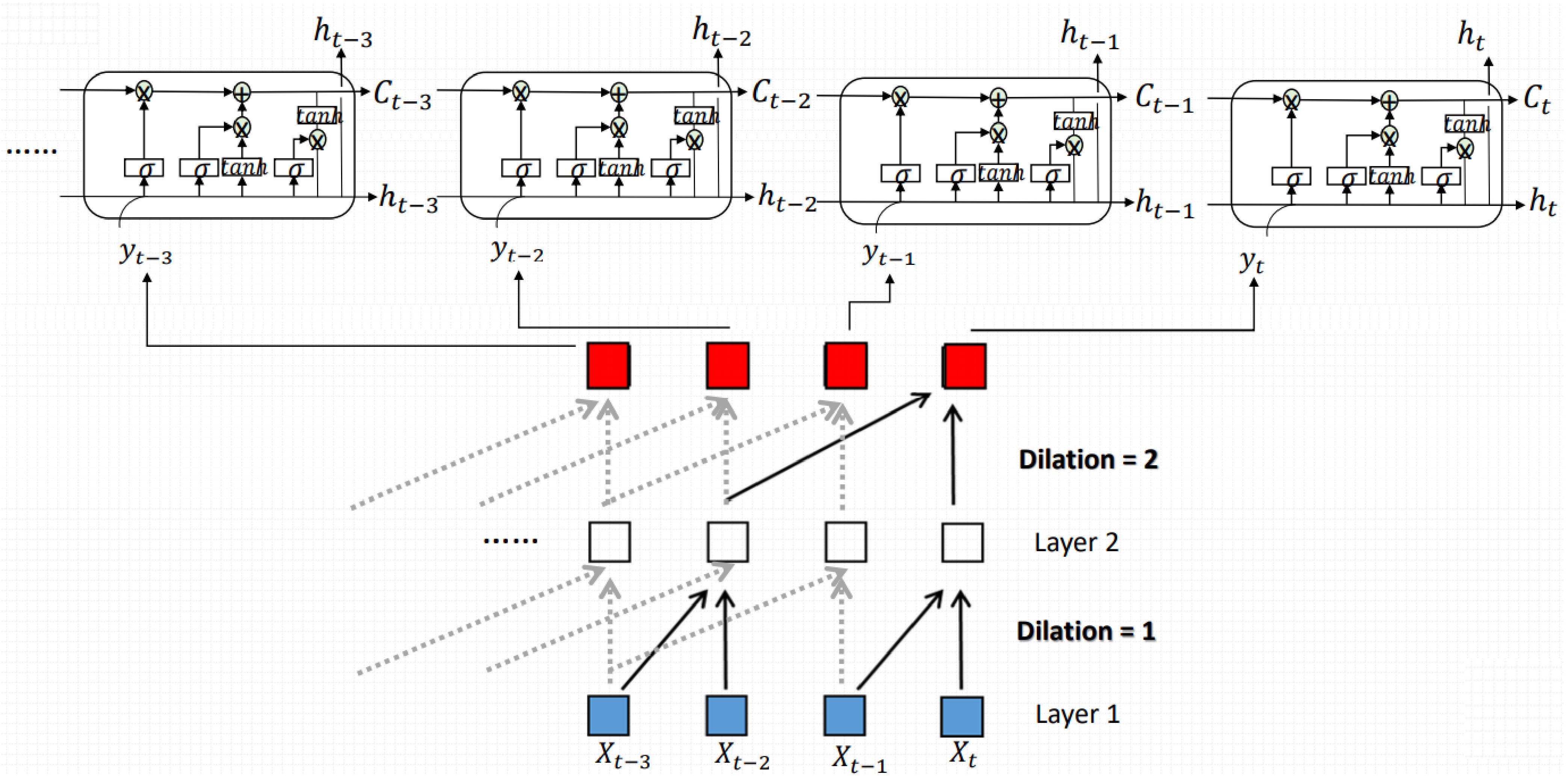
Temporal Convolution Networks (TCN)

(Dilation-causal convolution & Residual connection)

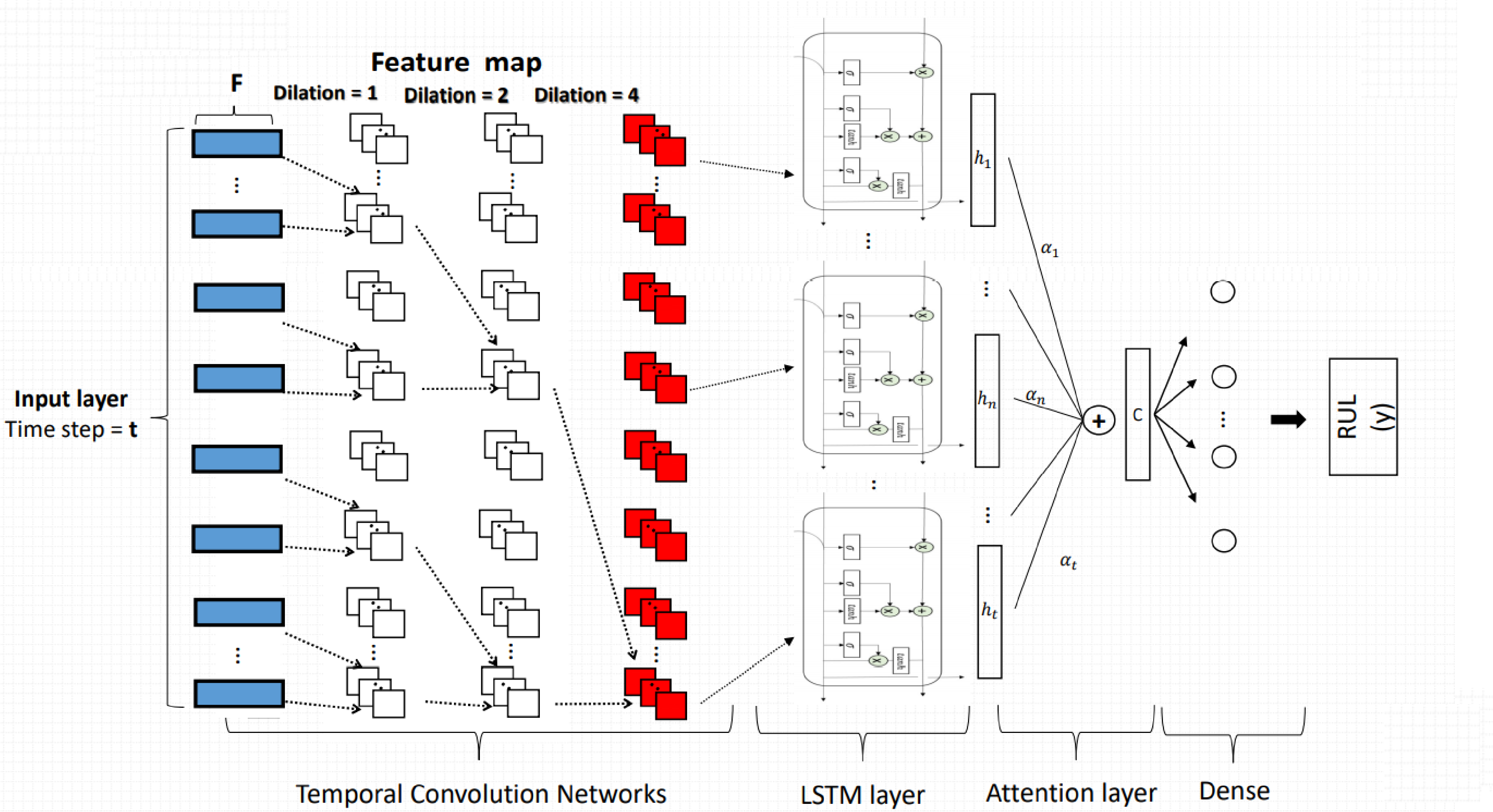


https://blog.csdn.net/Leon_winter/article/details/100124146

TCN-LSTM


h_{t-3}
C_{t-3}
h_{t-3}
y_{t-3}
h_{t-2}
C_{t-2}
h_{t-2}
y_{t-2}
h_{t-1}
C_{t-1}
h_{t-1}
y_{t-1}
h_t
C_t
h_t
y_t
tanh
σ
Dilation = 2
Layer 2
Dilation = 1
Layer 1
X_{t-3}
X_{t-2}
X_{t-1}
X_t

TCN-LSTM



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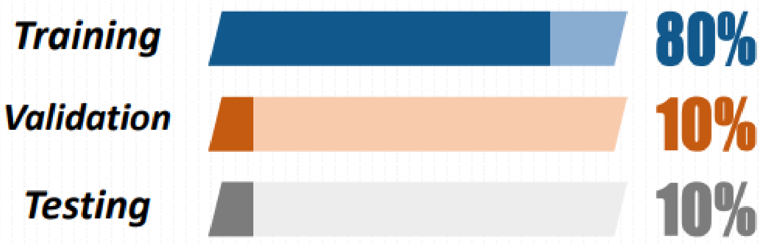
TCN-LSTM

Case study – RUL prediction for Ion mill etching tool

- Three models are used to predict three type of fault.
- For each cycle, only 3000 seconds are used before the failure.
- Smooth length = 1
- T (window size) = 500



Fault type	cycle
flow cool leak	54
flow cool pressure too high	53
flow cool pressure dropped below limit	69

Symbol	Features
X1	ION GAUGE PRESSURE
X2	ETCH BEAM VOLTAGE
X3	ETCH BEAM CURRENT
X4	ETCH SUPPRESSOR VOLTAGE
X5	ETCH SUPPRESSOR CURRENT
X6	FLOW COOL FLOW RATE
X7	FLOW COOL PRESSURE
X8	ETCH GASCHANNEL1 READBACK
X9	ETCH PBN GAS READBACK
X10	FIXTURES HUTTER POSITION

Source: https://www.phmsociety.org/events/conference/phm/18/data-challenge

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TCN-LSTM

Experiment result
(Ion mill etching tool dataset)

	Random Forest		Xgboost		MLP		LSTM		TCN		TCN-LSTM		TCN-LSTM with attention	
Fault type	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Flow cool pressure dropped below limit	1036.97	1267.84	996.66	1238.81	836.94	1001.44	597.37	801.87	512.64	627.75	478.94	607.97	474.76	601.46
Flow cool pressure too high	1175.11	1384.81	1424.00	1157.27	1040.15	1214.11	676.19	863.88	655.17	802.30	638.58	818.61	609.86	748.12
Flow cool leak	869.61	1176.56	865.51	1130.95	811.22	1042.41	642.43	768.41	462.90	649.00	621.48	858.42	428.83	541.24

01

TCN-LSTM with attention is better than other deep learning methods.

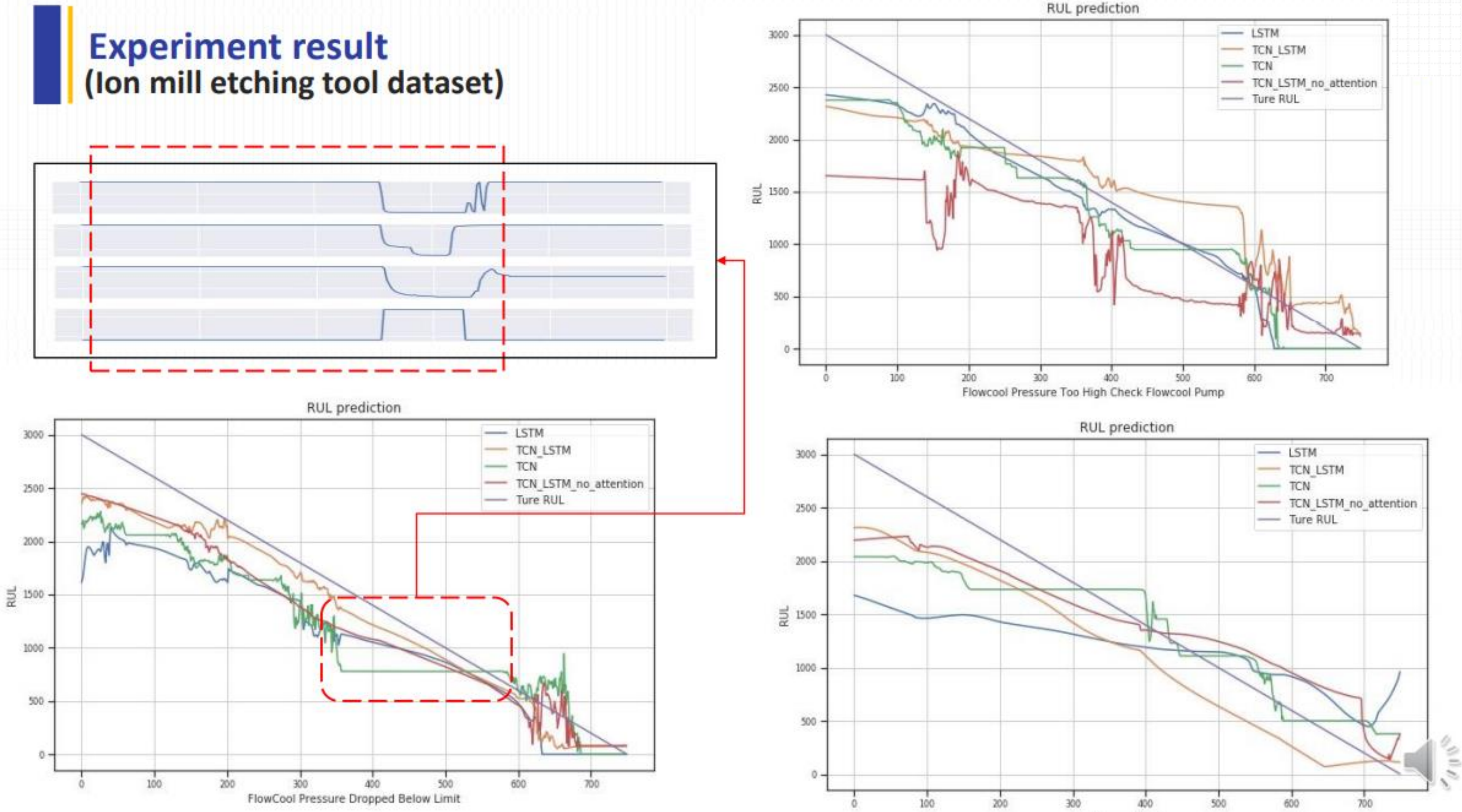
02

The experimental results show that the machine learning method is worse than the deep learning method in predicting the remaining life without any feature engineering.

03

We compared the TCN-LSTM model between attention mechanism and no attention mechanism, The experimental results show the model with attention mechanism is better.

TCN-LSTM



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