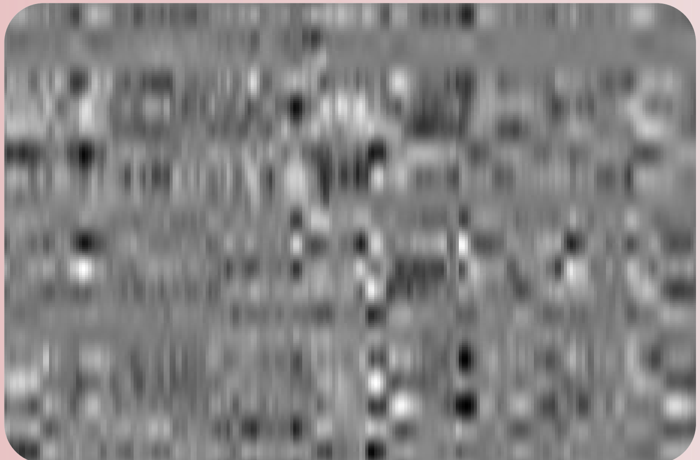
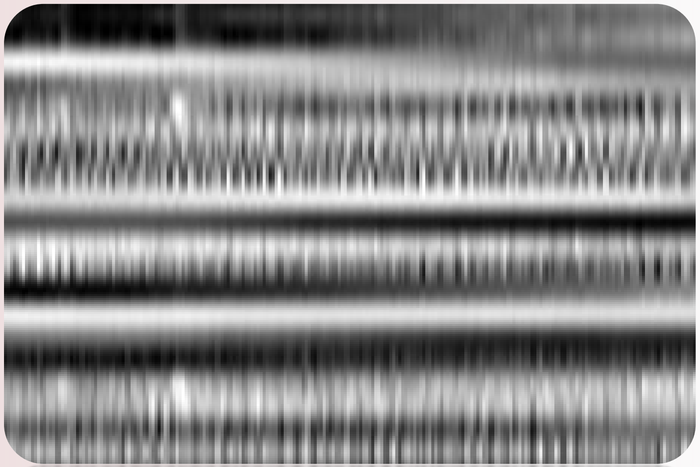
Low Latency Real-Time Seizure Detection Using Transfer Deep Learning





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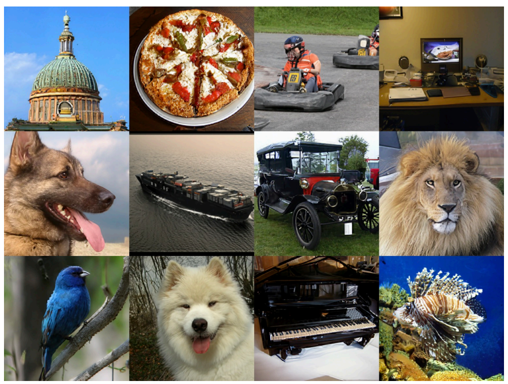
Abstract

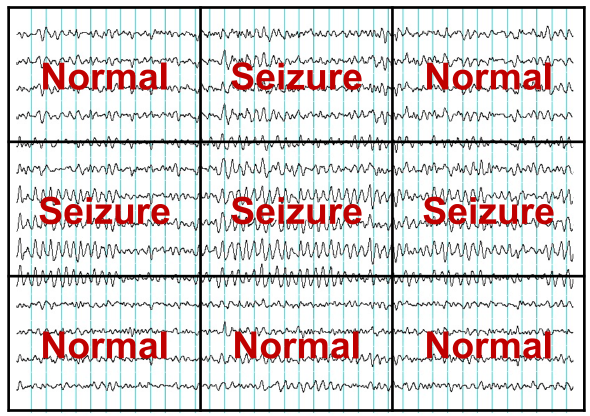
- Scalp electroencephalogram (EEG) signals have a low signal-to-noise ratio.
- Temporal and spatial information must be exploited to achieve accurate detection of seizure events.
- Most popular approaches to seizure detection using deep learning do not jointly model this information or require multiple passes over the signal, which makes the systems inherently non-causal.
- We exploit spatiotemporal information by converting the multichannel signal to a grayscale image and using transfer learning to achieve high performance.
- The proposed system is trained end-to-end with only very simple pre- and post-processing operations which are computationally lightweight and have low latency, making them conducive to clinical applications that require real-time processing.
- We have achieved a performance of 42.05% sensitivity with 5.78 false alarms per 24 hours on the development dataset of v1.5.2 of the Temple University Hospital Seizure Detection Corpus.
- On a single core CPU operating at 1.7 GHz, the system runs faster than real-time (0.58 xRT), uses 16 Gbytes of memory, and has a latency of 300 msec.

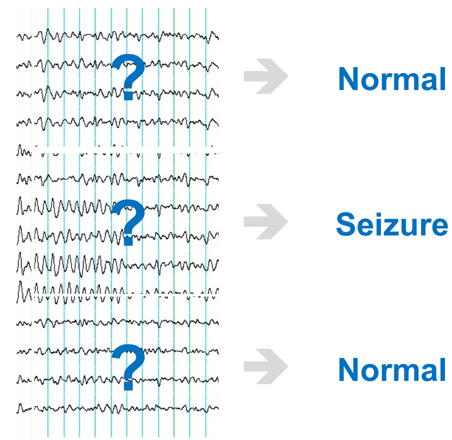
Introduction: Visual Interpretation of an EEG

Manual Interpretation

Human Vision → Train to Visually Interpret EEG → Expert Interpreter of EEG



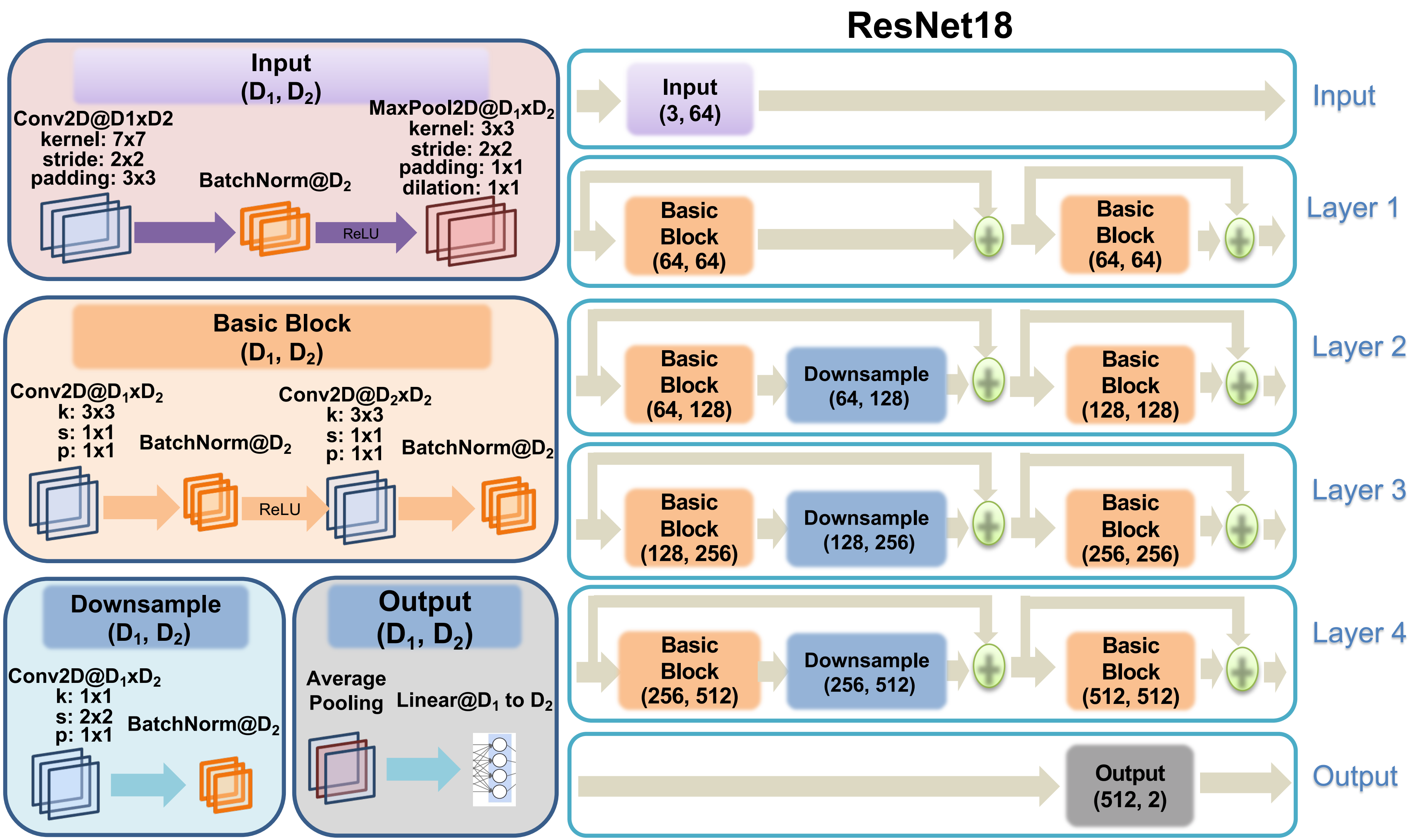




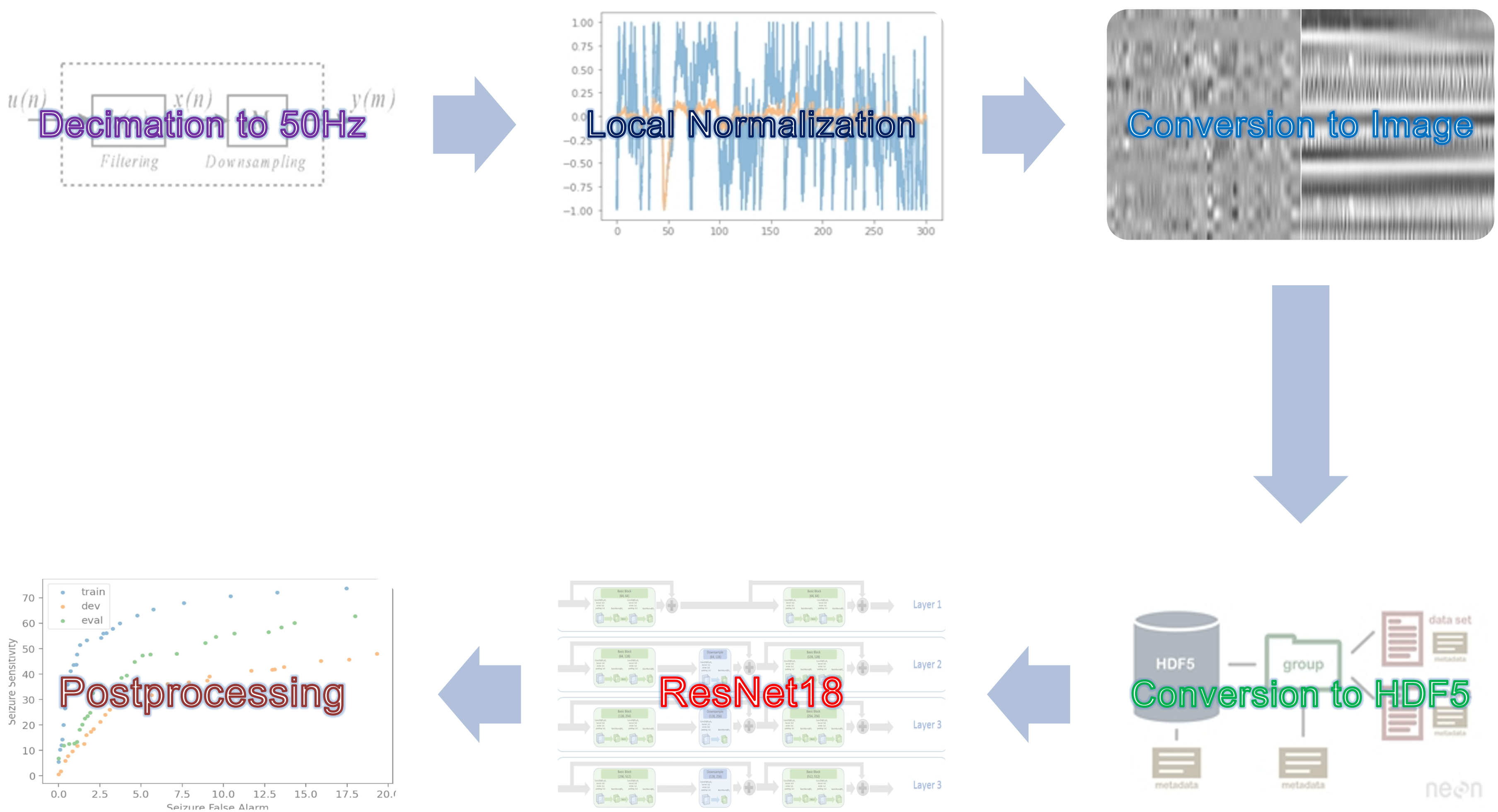
ImageNet Pretrained Network → EEG Adaptation Training → Machine Interpretation

Automatic Interpretation

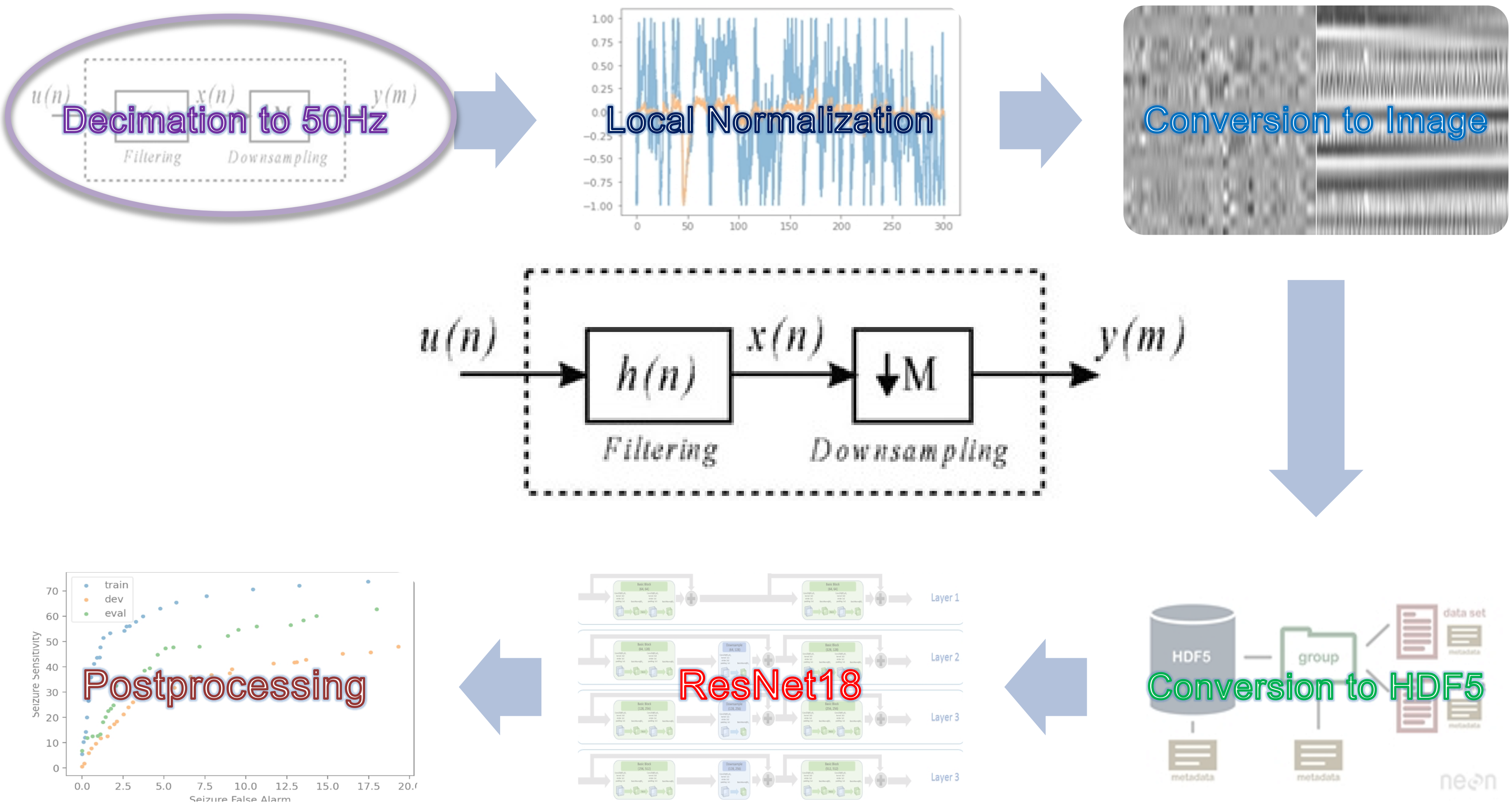
Transfer Learning: Leveraging Pretrained Networks



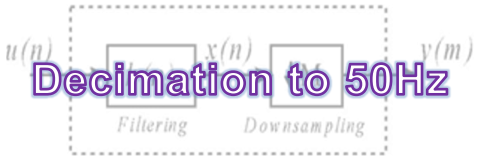
Processing Pipeline: An Overview

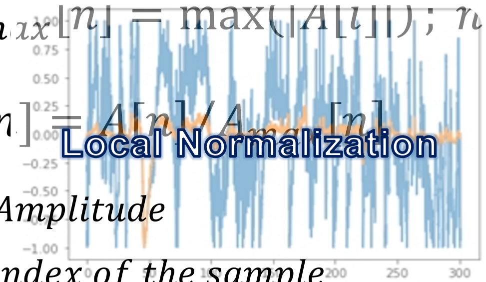


Processing Pipeline: Decimation



Processing Pipeline: Local Normalization





$$A_{max}[n] = \max(|A[i]|)\ ;\ n - {}^{N}\!/_{2} \le i \le n + {}^{N}\!/_{2}$$

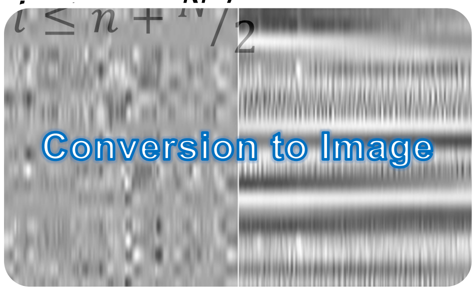
$$\hat{A}[n] = A[n]/A_{max}[n]$$

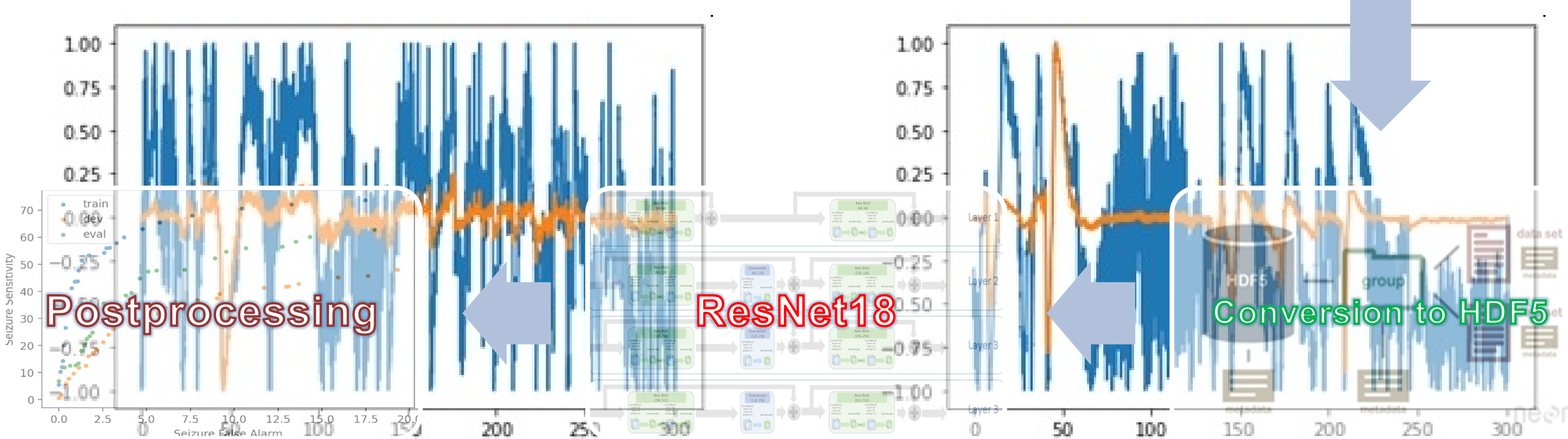
A: *Amplitude*

n: *index of the sample*

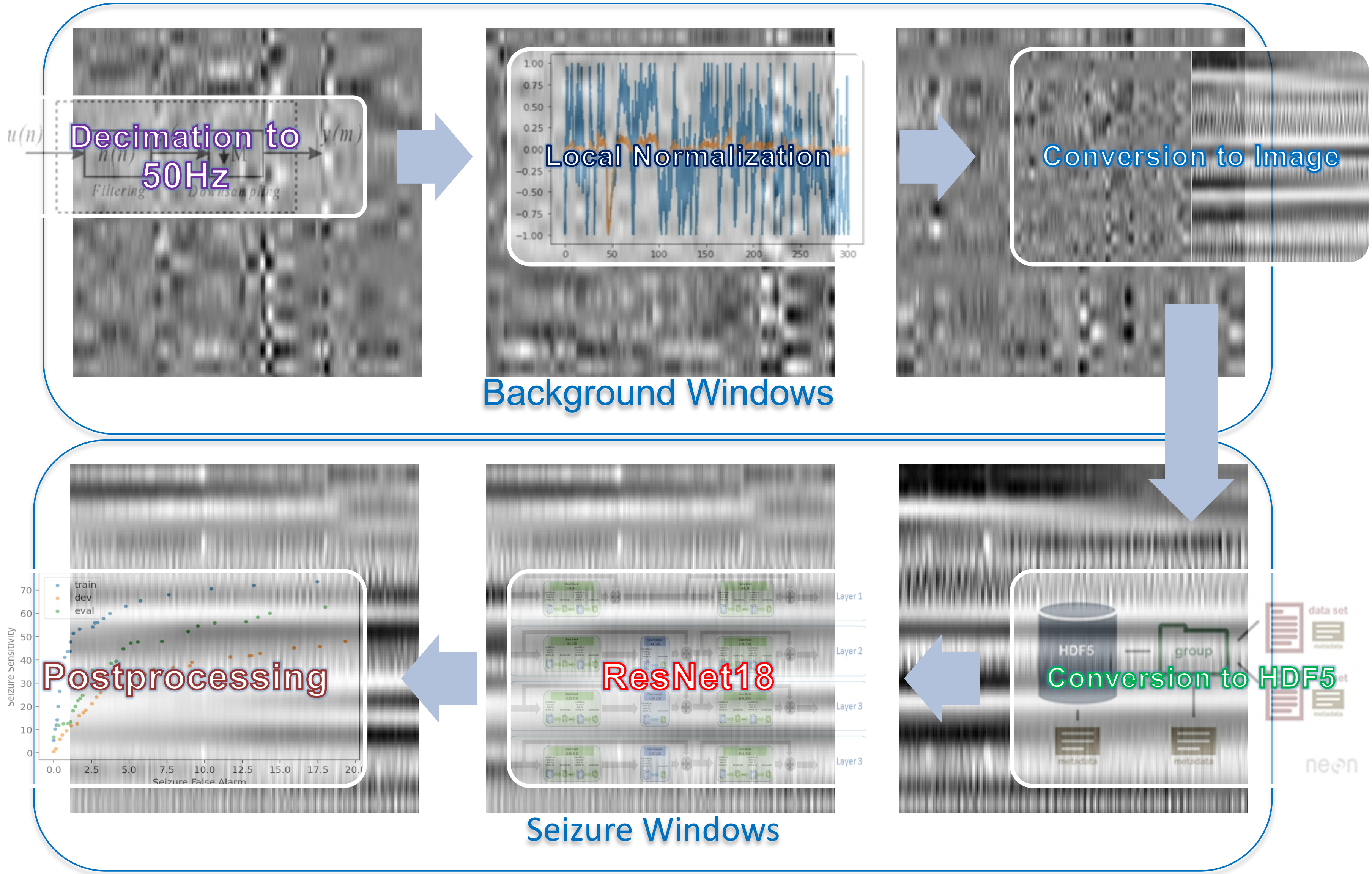
N: *number of samples in a window centered around current sample*

$\hat{A}[n]$: *Locally Scaled Image*



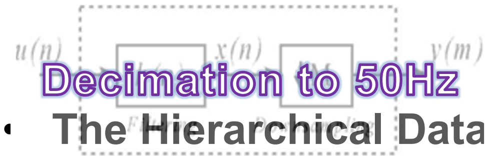


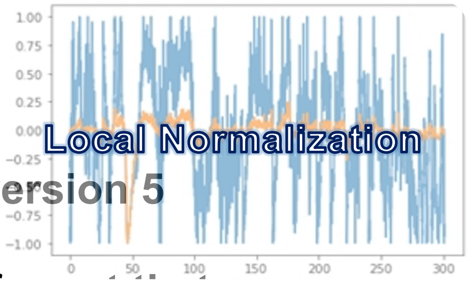
Processing Pipeline: Conversion to an Image

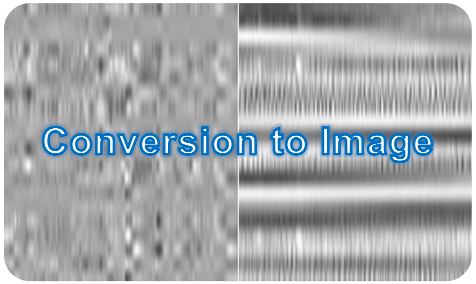


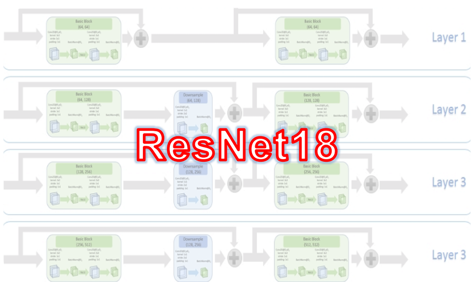
Processing Pipeline: Conversion to HDF5

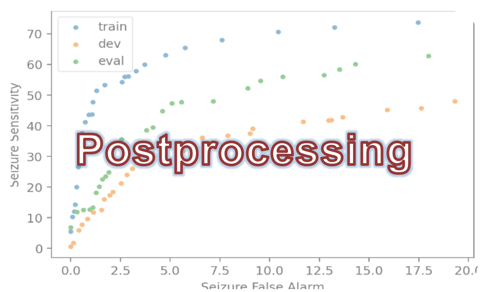
- The Hierarchical Data Format version 5 (HDF5), is an open-source file format that supports large, complex, heterogeneous data with fast read and write capabilities.











Processing Pipeline: Retraining ResNet18

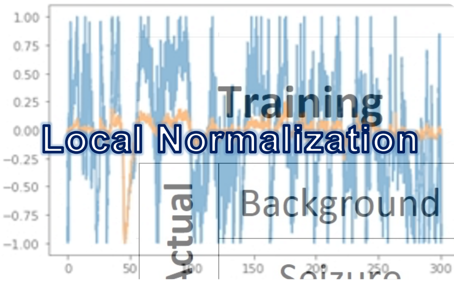
$$\omega_b = \frac{N_{seiz}}{N}, \qquad \omega_s = \frac{N_{bckg}}{N},$$

N: Total number of samples

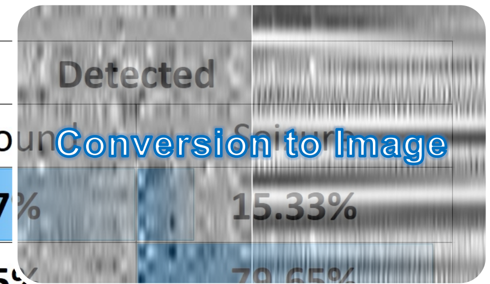
Decimation to 50Hz

N_{seiz}: Number of seizure samples

N_{seiz}: Number of background samples



Training		Detected	
		Background	Seizure
Actual	Background	84.67%	15.33%
	Seizure	20.35%	79.65%



$$loss_{weighted} = \omega_b * loss(x_i, b) + \omega_s * loss(x_i, s),$$

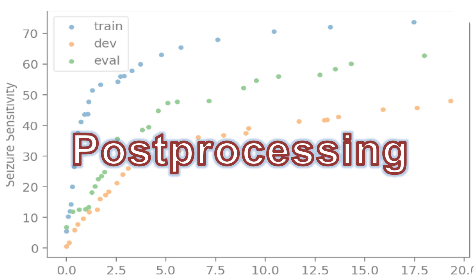
x_i: i^{th} input sample

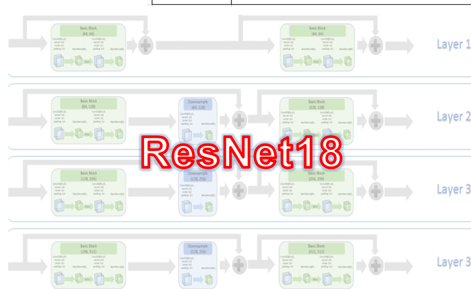
b: background index

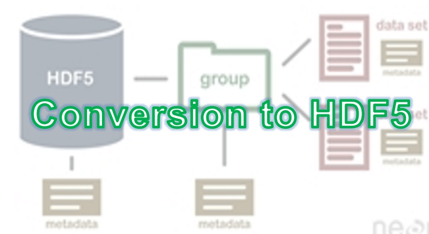
s: seizure index

$loss(x, y)$: cross entropy or mse

Development		Detected	
		Background	Seizure
Actual	Background	82.70%	[illegible]0%
	Seizure	39.53%	60.47%





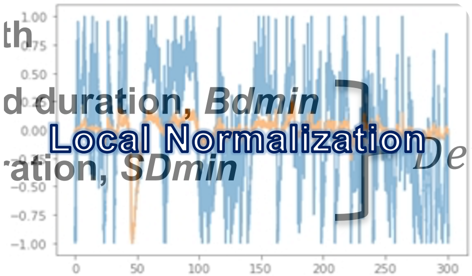


Processing Pipeline: Postprocessing

- Seizure confidence threshold, Sth
- Minimum acceptable background duration, *Bdmin*
- Minimum acceptable seizure duration, *SDmin*

$Detection\ Delay = BD_{min} + SD_{min}$

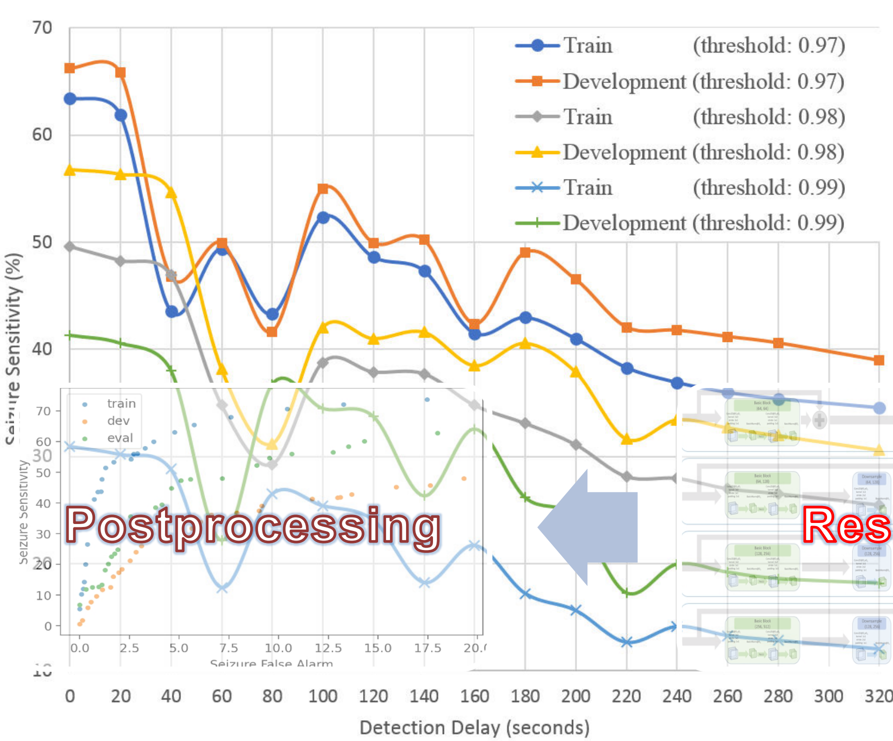
Decimation to 50Hz



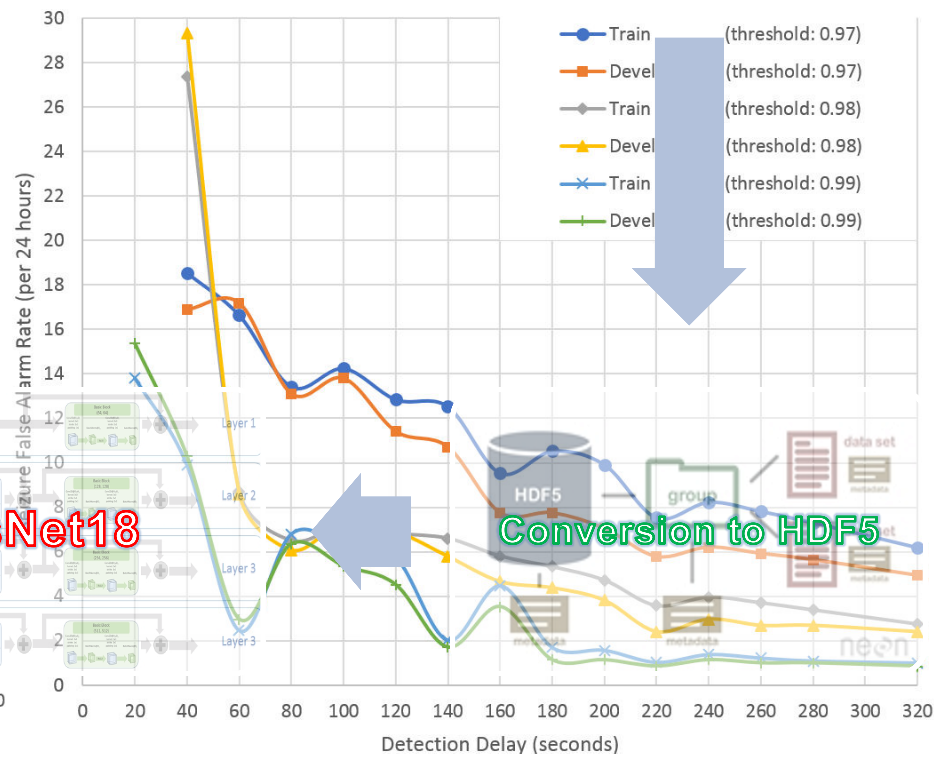
Local Normalization

Conversion to Image

Sensitivity



False Alarm



Postprocessing

ResNet18

Conversion to HDF5

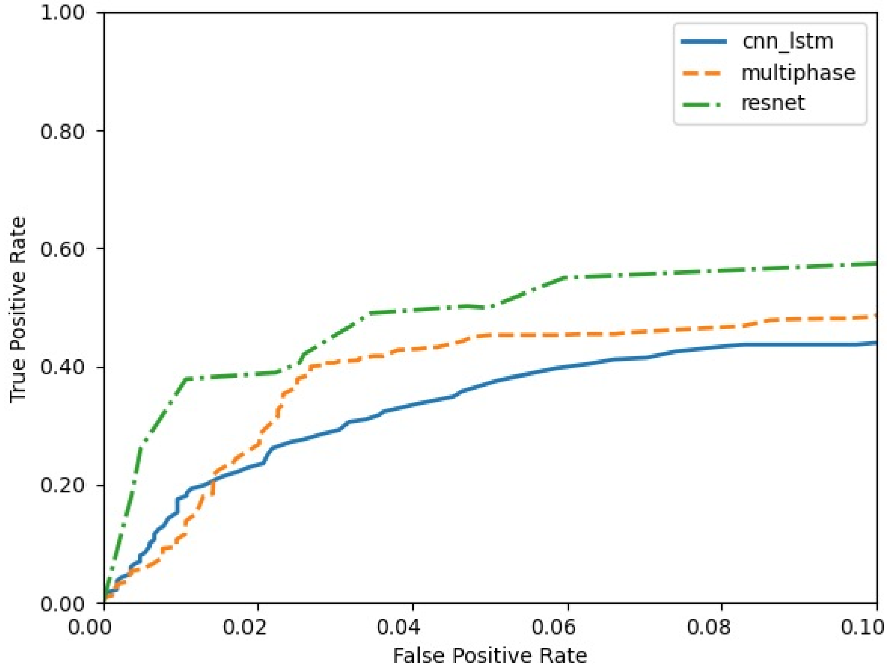
Results: Performance Comparison Using Overlap Scoring

Three systems were evaluated:

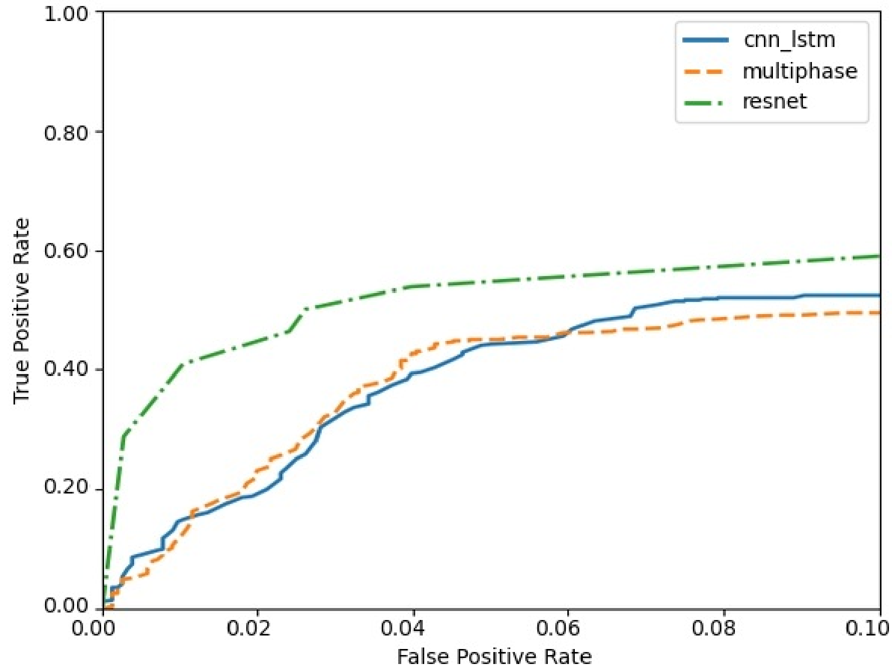
- **cnn_lstm:** a hybrid CNN/LSTM system
- **mphase:** a multipass system
- **resnet:** transfer learning

System	Sensitivity	FA Rate (/24H)
cnn_lstm	43.69%	20.85
mphase	40.12%	6.62
resnet	42.05%	5.78

Development Data



Evaluation Data



- **ResNet outperforms both of these systems when the FA rate is low.**

Results: Analysis of the False Positive Rate

- Comparison with two top systems in the Neureka™ 2020 Epilepsy Challenge.
- ResNet still lags the two best performing systems (sia and pnc98).
- The ResNet system runs faster than real time with a latency of 300 ms. The competition systems are non-real-time with infinite latency.

Development Data

	Metric	cnn lstm	multi phase	resnet	sia	pnc98
DPAL	Sens	45.17	36.70	20.36	23.45	6.98
	Spec	88.63	96.25	96.72	99.47	98.33
	FPs	23.25	6.76	5.50	0.97	2.54
EPCH	Sens	37.67	36.34	49.83	12.84	1.56
	Spec	96.56	97.16	92.64	99.97	99.99
	FPs	2686.97	2221.29	5753.08	25.85	8.45
OVLP	Sens	43.69	40.12	42.06	23.26	6.39
	Spec	91.71	97.19	97.40	99.74	99.65
	FPs	20.85	6.62	5.78	0.64	0.85
TAES	Sens	35.83	32.27	15.34	11.38	2.04
	Spec	83.91	90.18	88.81	99.46	99.42
	FPs	32.55	18.07	19.42	0.99	0.87
	WGT	-53.05	-21.21	-40.71	2.59	0.83

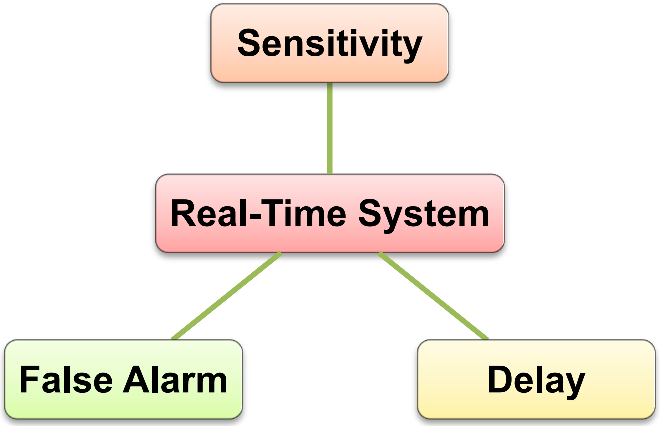
Evaluation Data

	Metric	cnn lstm	multi phase	resnet	sia	pnc98
DPAL	Sens	54.79	45.01	14.29	24.07	8.61
	Spec	90.41	94.47	98.03	99.31	99.44
	FPs	21.79	11.61	3.50	1.27	0.95
EPCH	Sens	38.15	52.04	42.82	1.27	5.09
	Spec	98.40	98.27	95.88	99.95	100.00
	FPs	1282.04	1391.52	3314.04	43.23	2.07
OVLP	Sens	51.47	44.62	37.18	23.88	8.41
	Spec	92.63	95.48	98.33	99.61	99.93
	FPs	19.25	11.45	3.82	0.96	0.16
TAES	Sens	39.46	37.80	10.97	12.37	2.04
	Spec	87.49	91.29	93.51	99.22	99.90
	FPs	28.21	18.39	11.82	1.44	0.17
	WGT	-38.57	-16.58	-26.08	2.46	0.82

Conclusions

- **Transfer deep learning is used to improve spatiotemporal modeling and accelerate convergence during training.**
- **Through the optimization of three critical parameters:**
  - **Sensitivity**
  - **False Alarm Rate**
  - **Detection Latency**

  real-time performance comparable to offline systems, can be achieved on v1.5.2 of the TUH EEG Seizure Detection Corpus without sacrificing performance:
  - **Sensitivity: 42.05%**
  - **False Alarm Rate: 5.78 false alarms per 24 hours**
- **While the number of samples in our database is relatively large, we do observe overfitting tendencies on the training dataset.**
- **Though cross-validation was used, we plan to explore other pretrained ImageNet networks to avoid overfitting and improve generalization.**



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- **NEDC's data and resources are freely available at:**

  https://www.isip.piconepress.com/projects/tuh_eeg/html/downloads.shtml

Brief Bibliography

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