Weakly-supervised learning for emboli characterization with Transcranial Doppler (TCD) monitoring

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Collaborators: Marilys Almar[3]

Doctoral School: EEA

Funding: Regional Project CAREMB

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[2] Université de Technologie de Troyes, Laboratoire Informatique et Société Numérique, Troyes, France
[3] Atys Medical, Soucieu-en-Jarrest, France

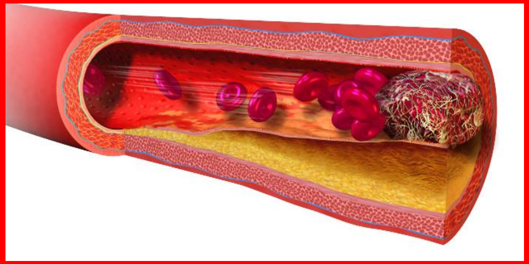
Outline

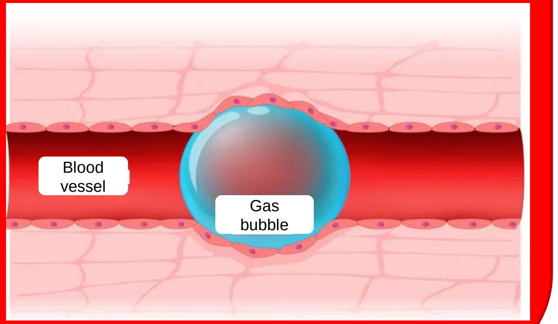
Outline

WHAT ?

WHAT ?

Emboli





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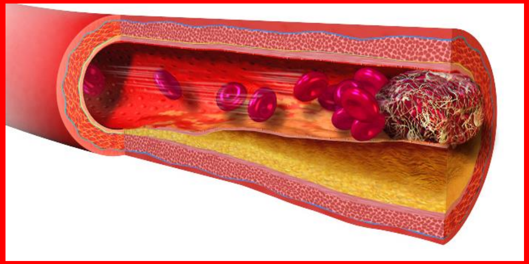
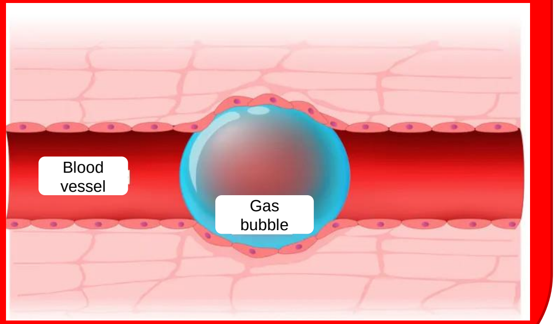
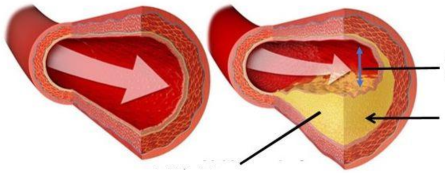




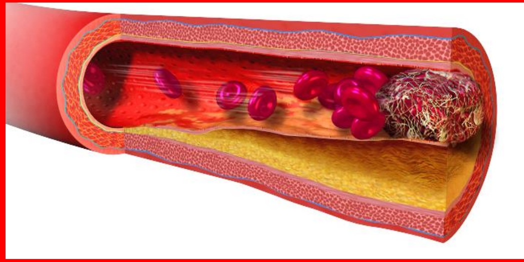
Sources

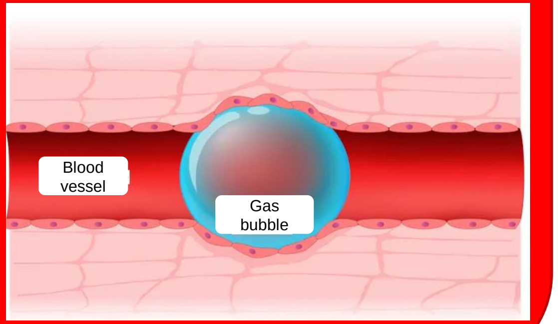


Atherosclerosis

WHAT ?

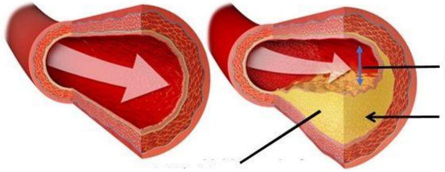
Emboli





Sources

Normal Artery   Narrowing Artery

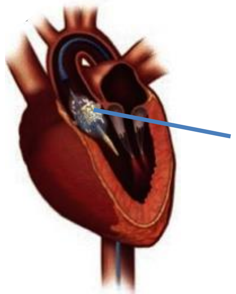


Narrowing of the arterial lumen

Possible partial detachment of the plaque

Lipid/calcium deposit

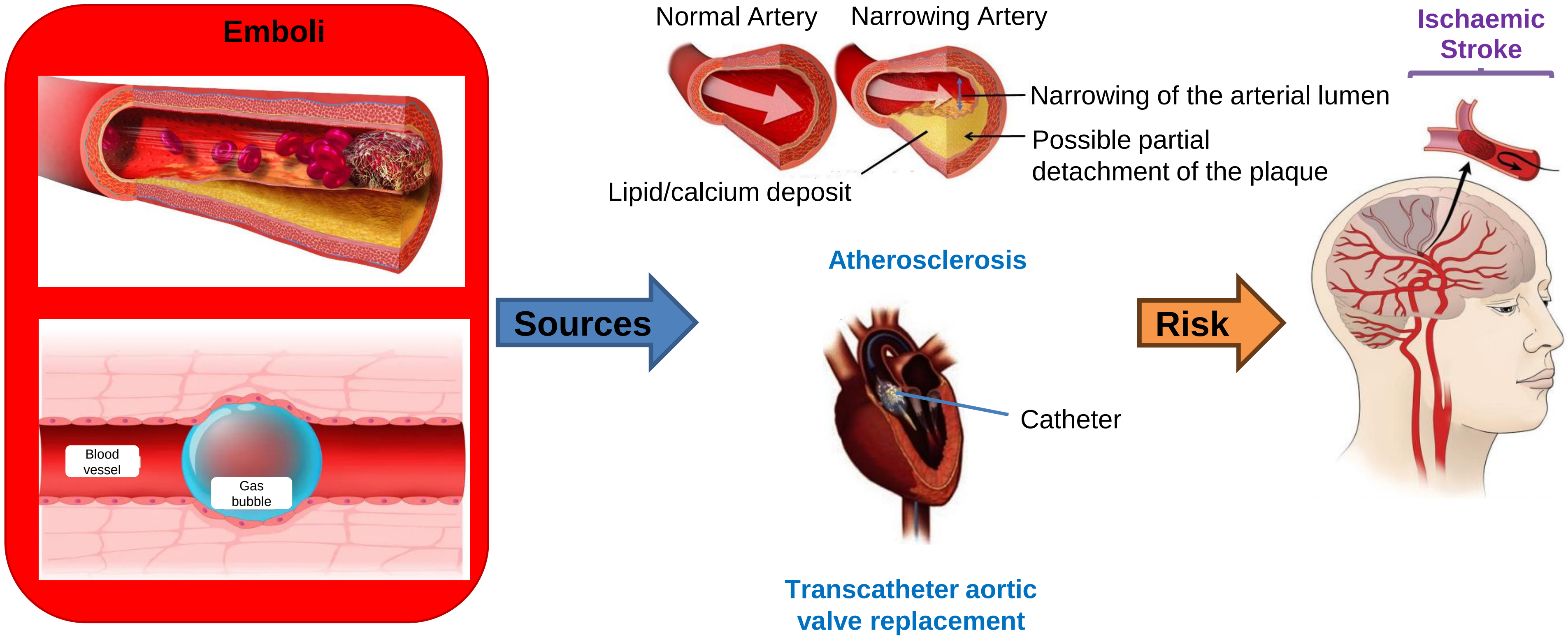
Atherosclerosis



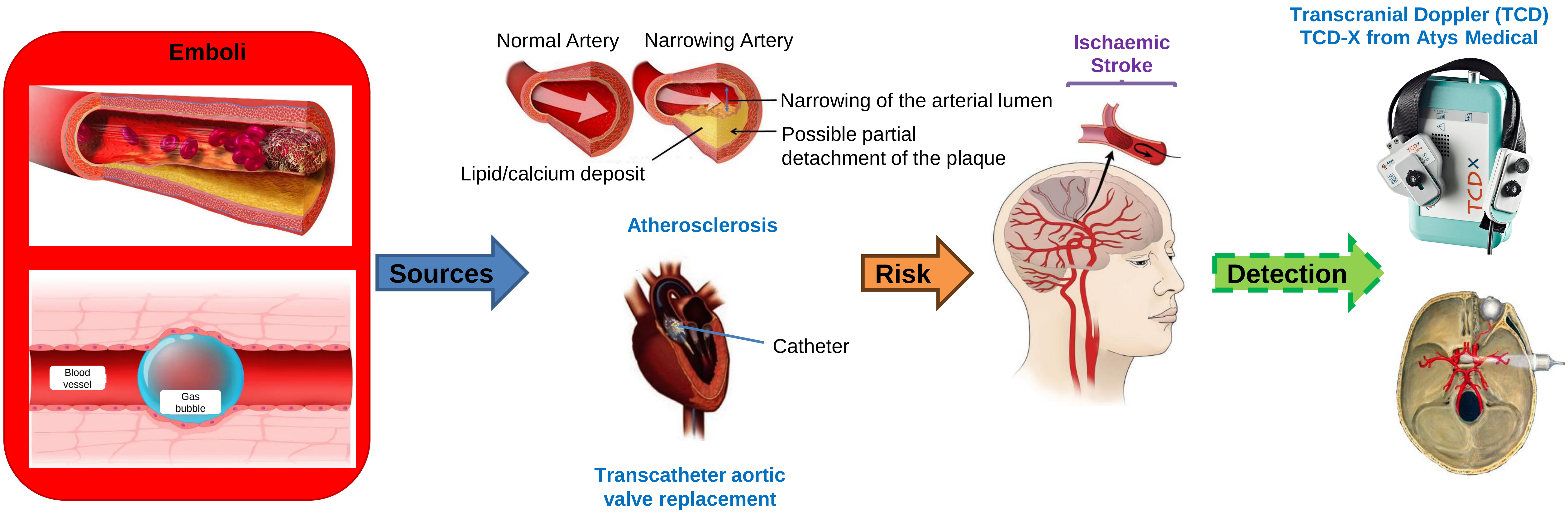
Catheter

Transcatheter aortic valve replacement

WHAT ?


Emboli
Blood vessel
Gas bubble
Sources
Normal Artery
Narrowing Artery
Narrowing of the arterial lumen
Possible partial detachment of the plaque
Lipid/calcium deposit
Atherosclerosis
Catheter
Transcatheter aortic valve replacement
Risk
Ischaemic Stroke

WHAT ?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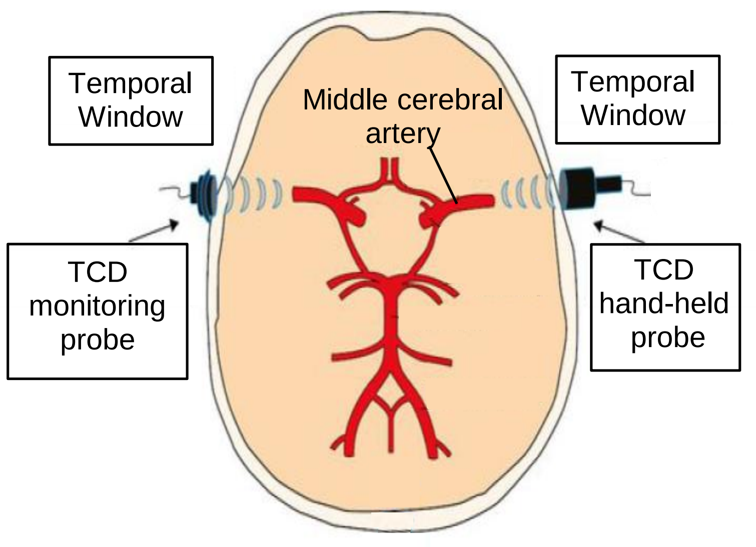
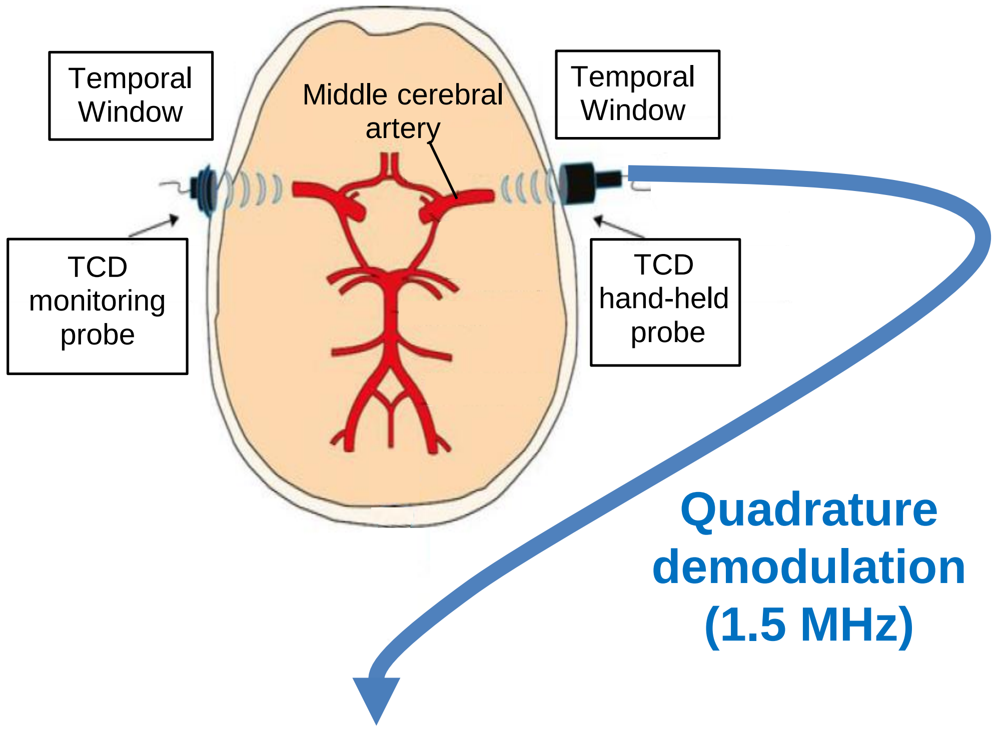
Risk
Ischaemic Stroke
Detection
Transcranial Doppler (TCD)
TCD-X from Atys Medical
TCD-X

How ?

How ?

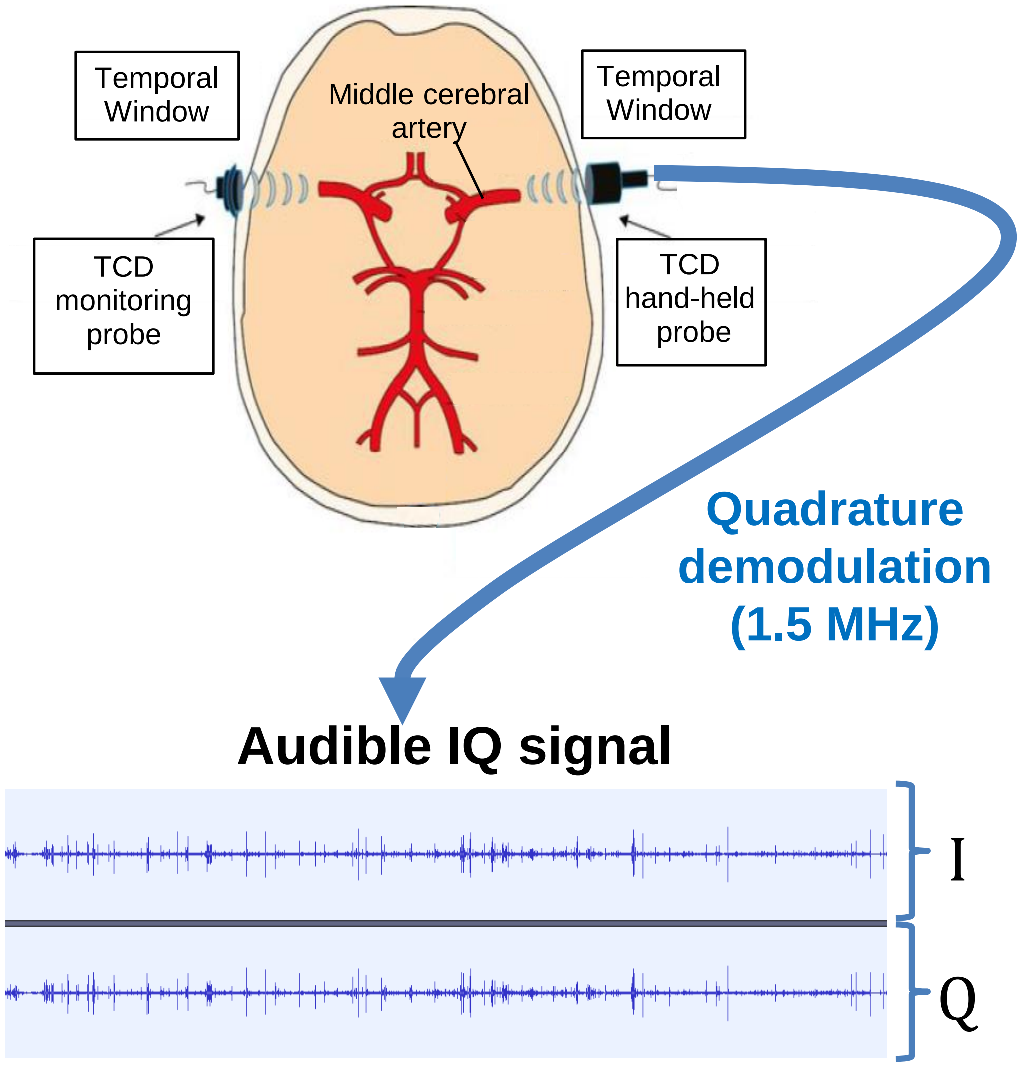

Temporal Window
Middle cerebral artery
Temporal Window
TCD monitoring probe
TCD hand-held probe

How ?



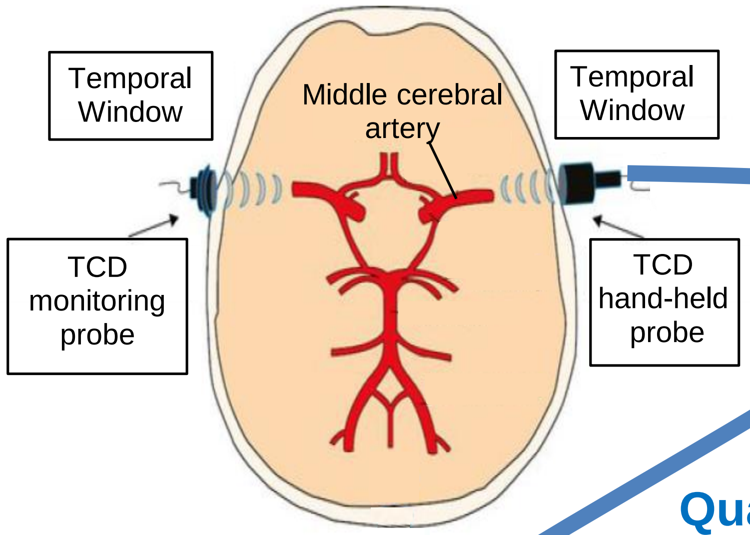
Quadrature demodulation (1.5 MHz)

How ?



$$S_C = I + i \times Q$$

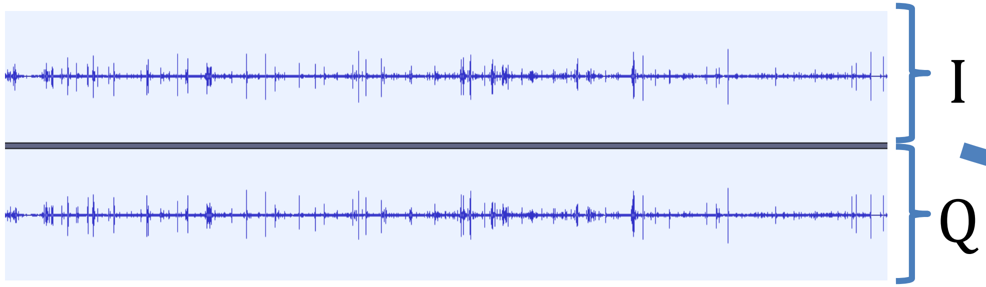
How ?



Quadrature demodulation (1.5 MHz)

Raw Doppler Signal

Audible IQ signal



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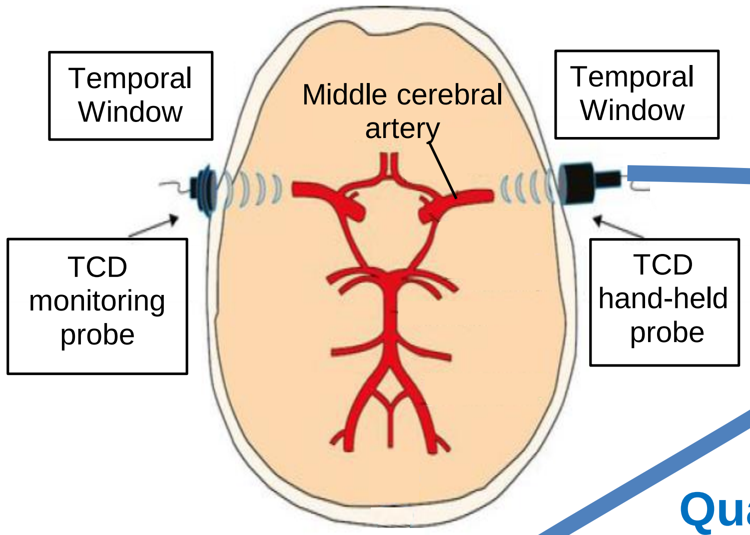

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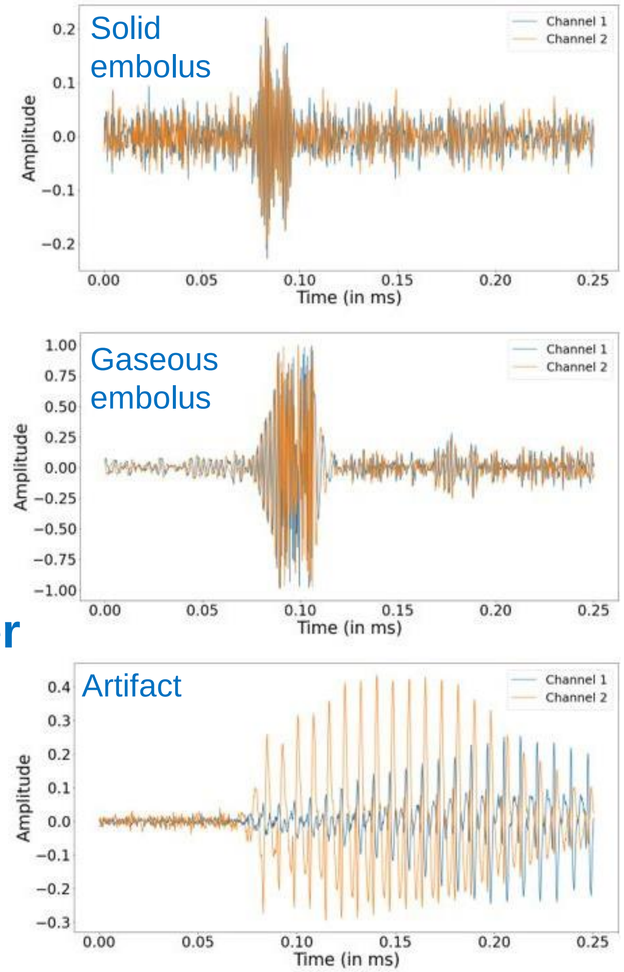

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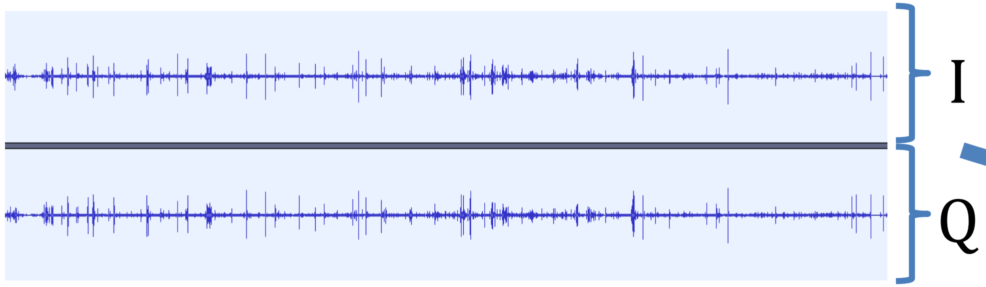

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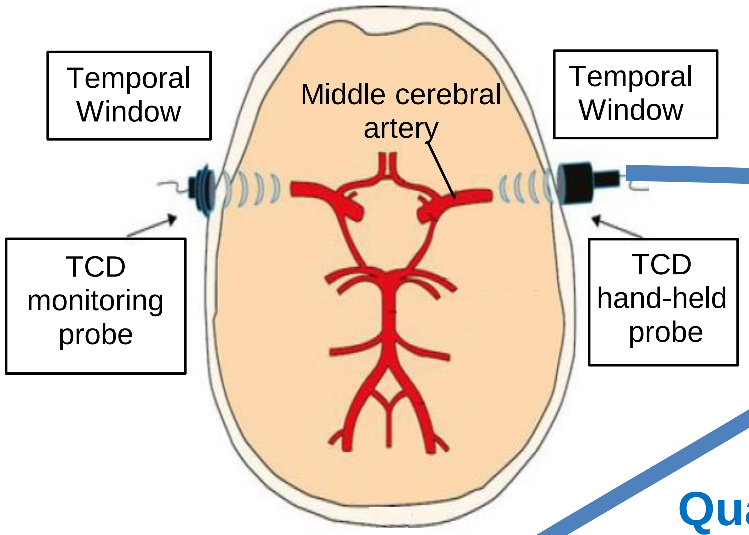

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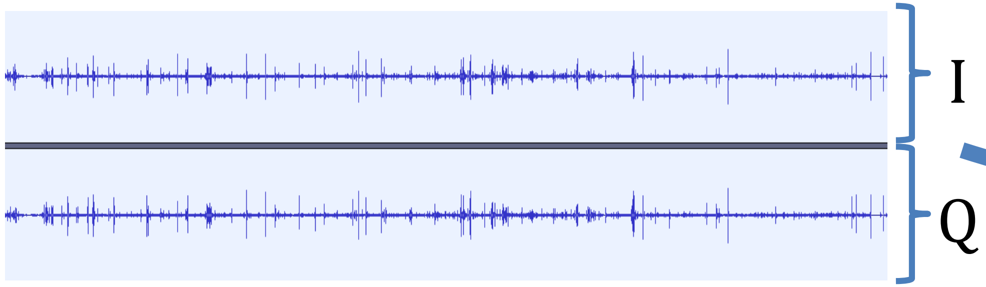

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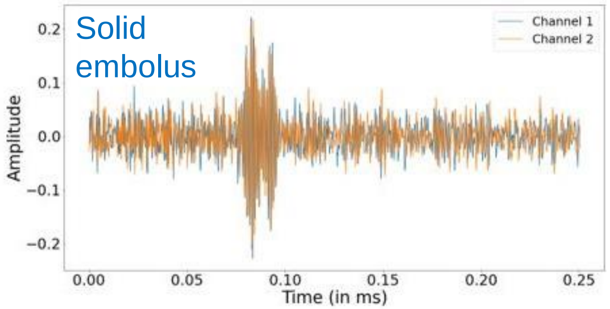
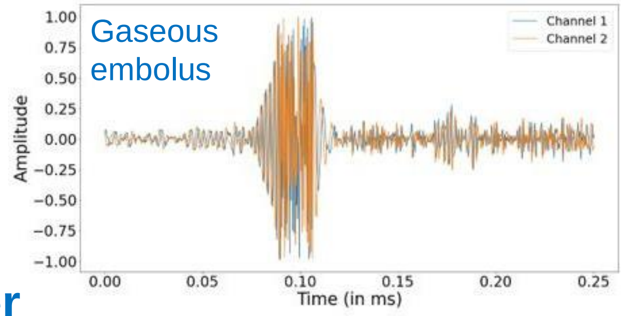
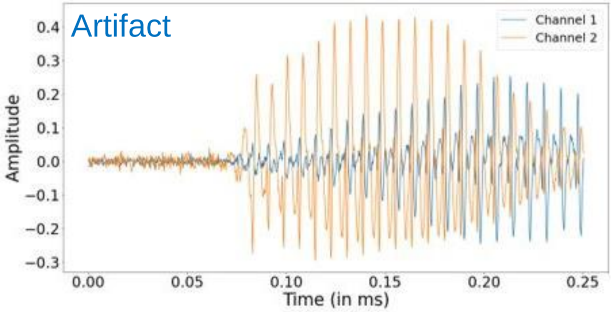
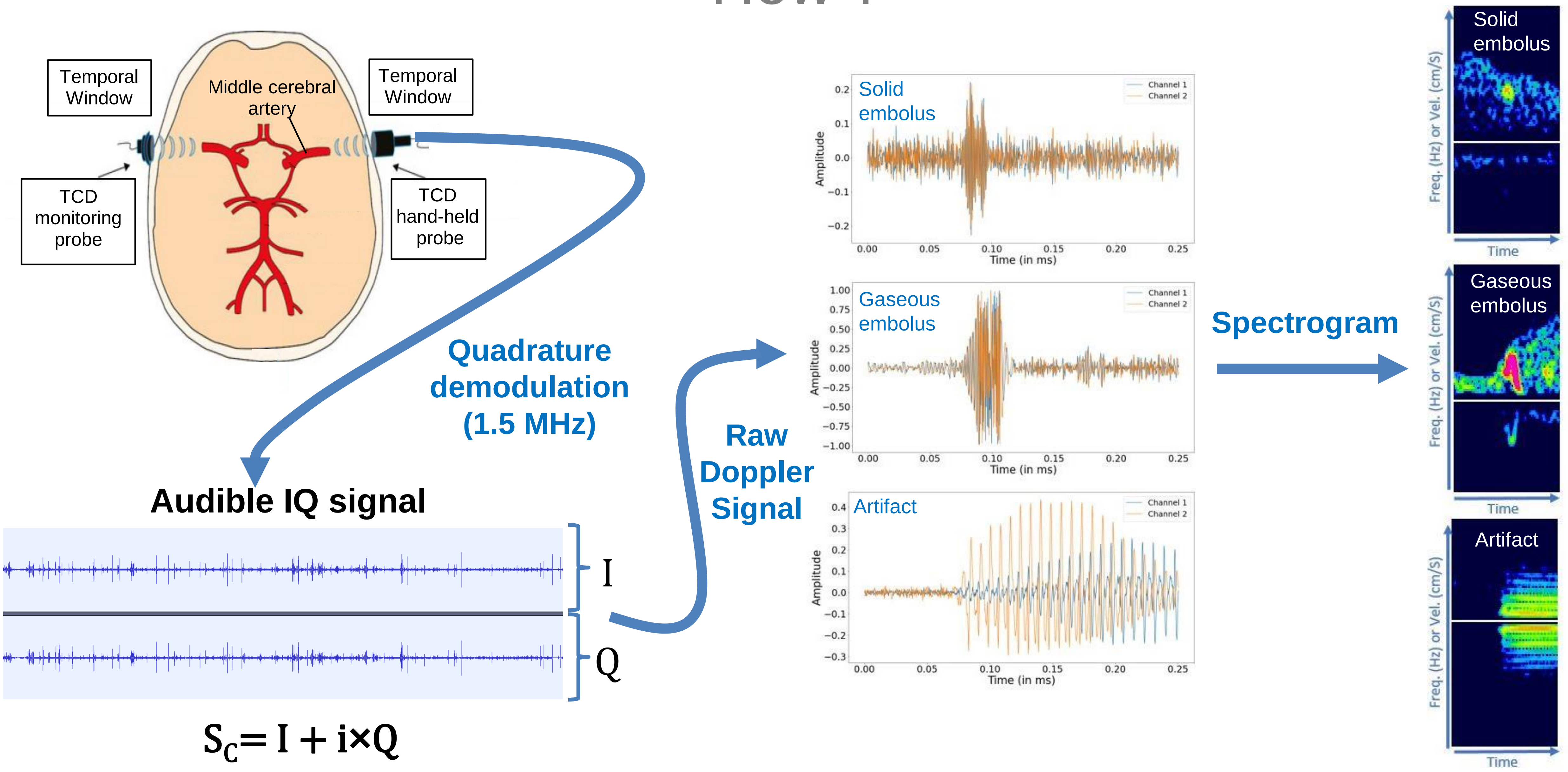






Spectrogram

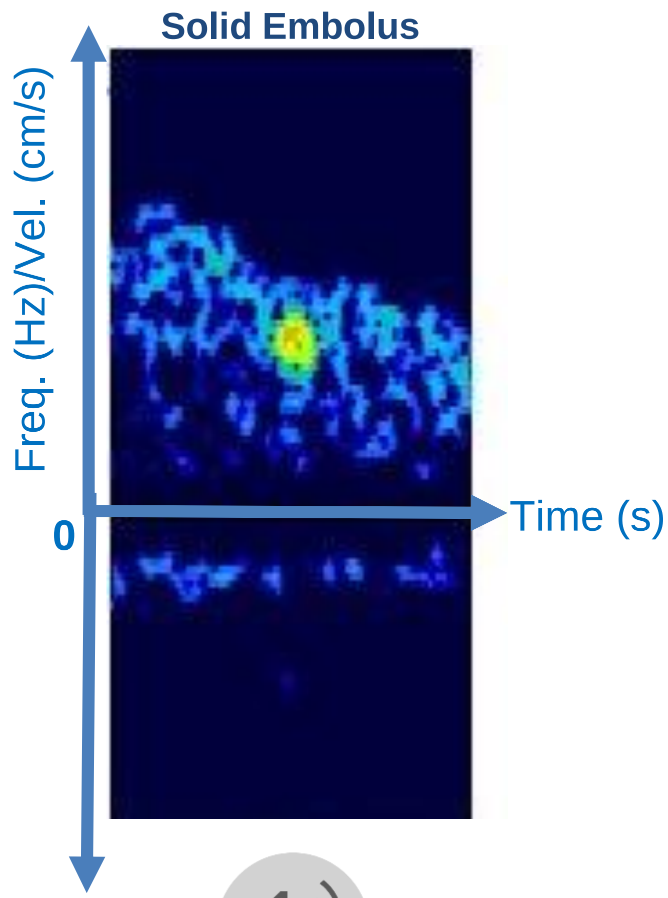
How ?



$$S_C = I + i \times Q$$

Emboli detection criteria

- **Basic identification criteria of Doppler microembolic signals***
  - **Duration < 300 ms** ⇒ High intensity transient signals (**HITS**)
  - **Unidirectional** in the time-frequency domain.
    - ⇒ **No symmetry** with respect to the zero-frequency baseline.
  - **Musical** "chirp" or "snap" **sound**.
  - **Intensity increase** of at least **3dB** with respect to the blood flow signal.
    - ⇒ Defined through the hits-to-blood ratio (**HBR**)



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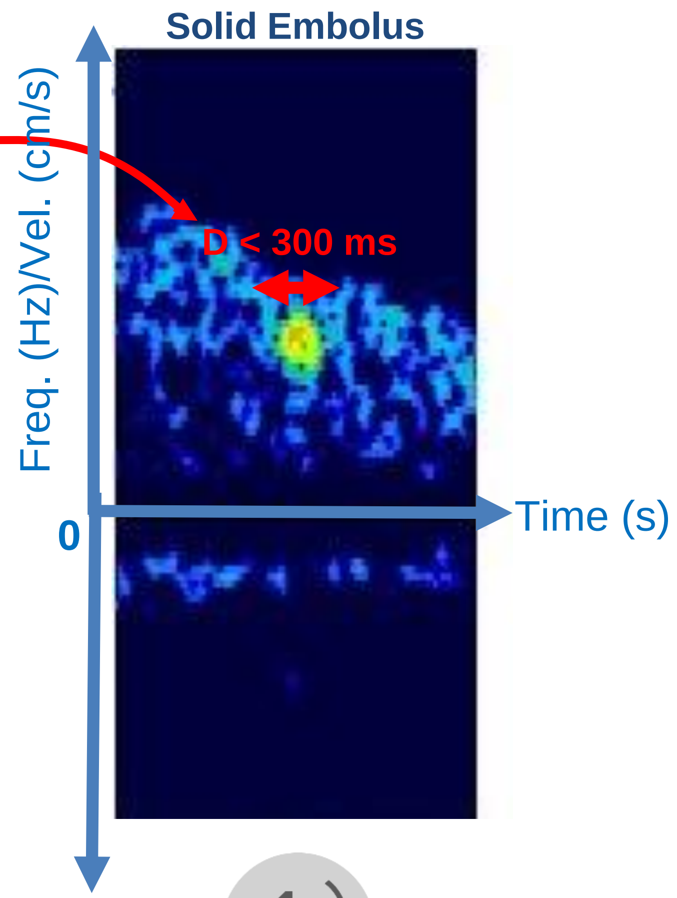

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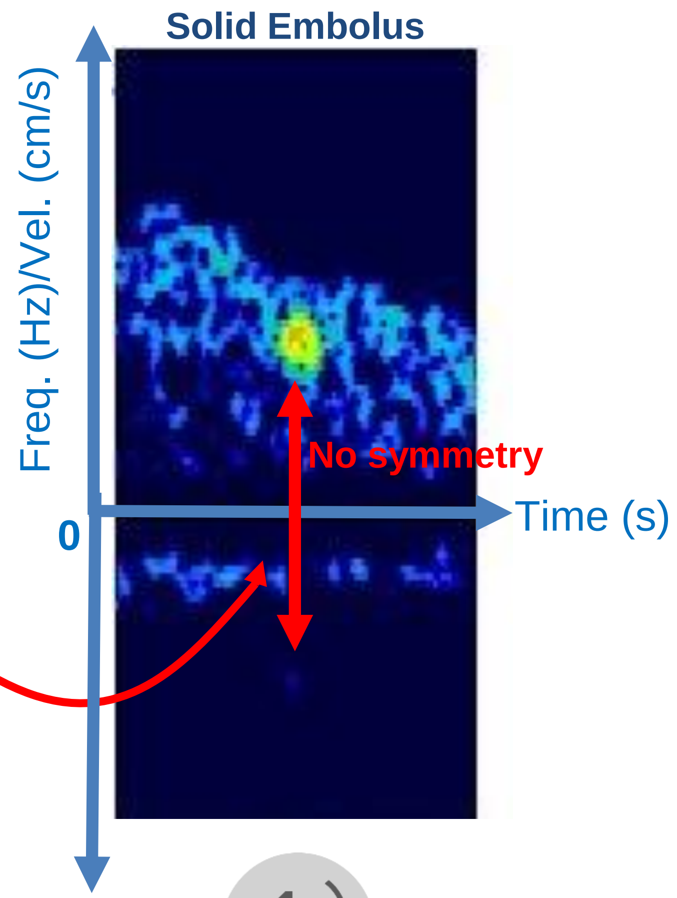

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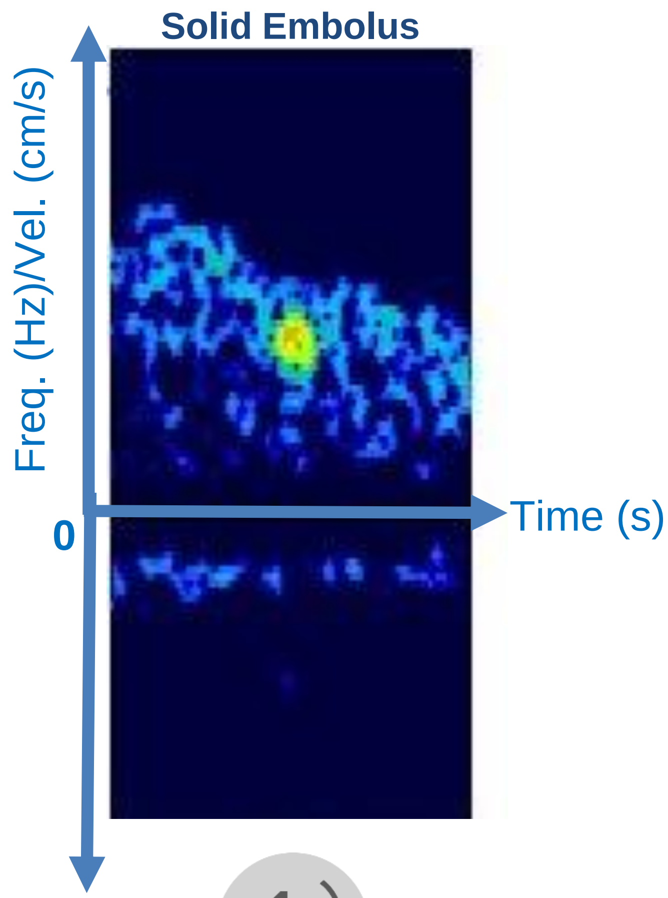

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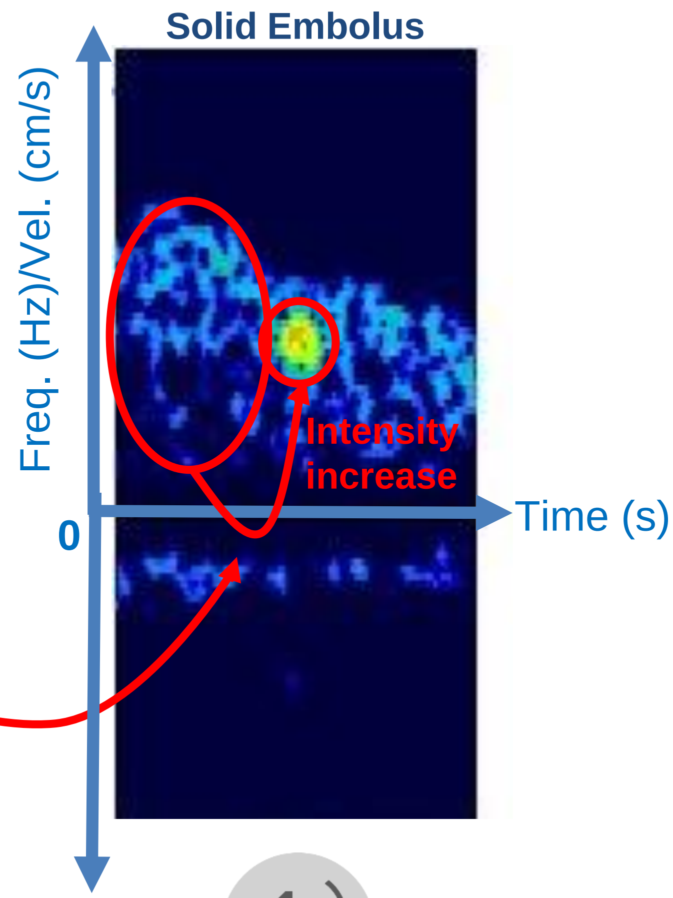

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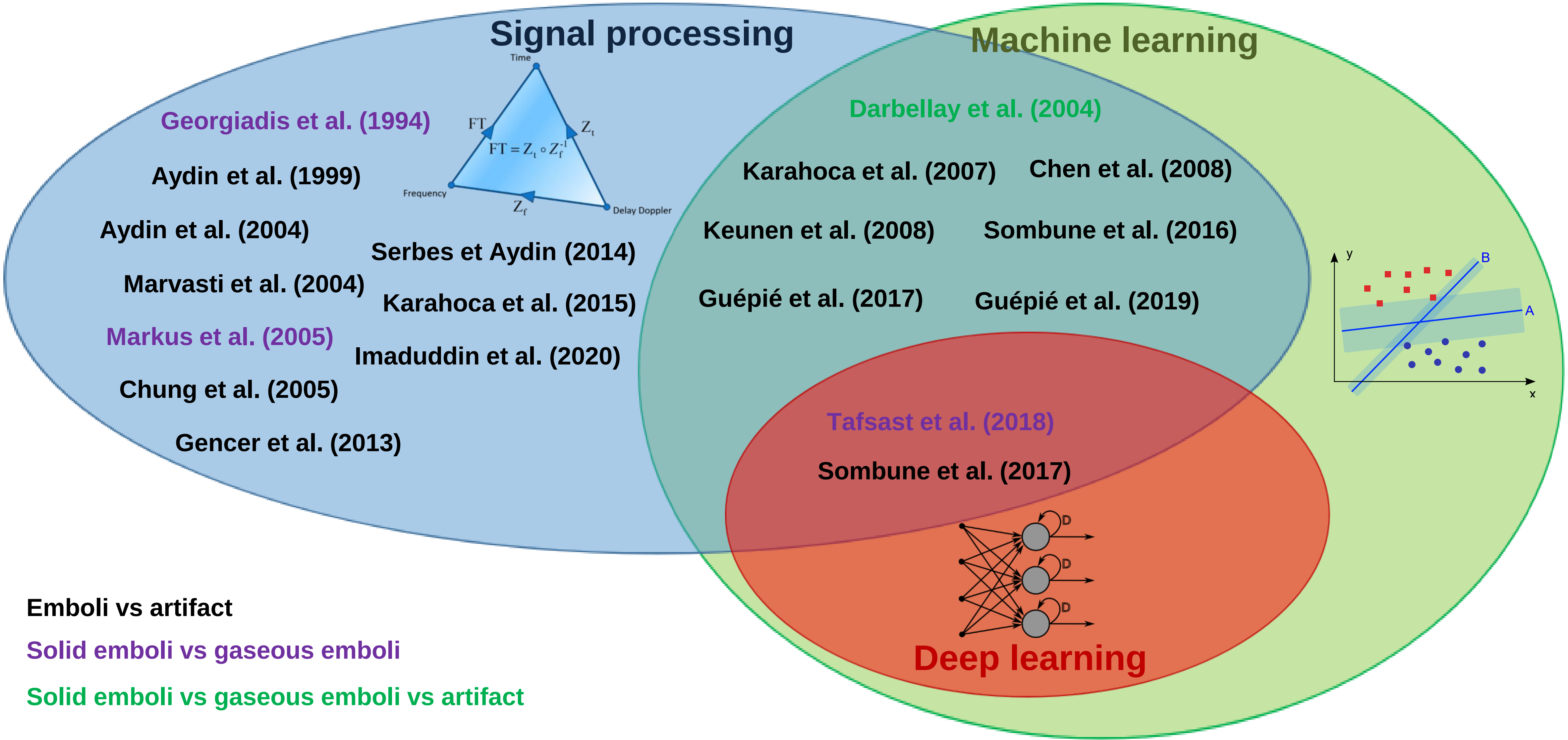
Outline

Emboli classification



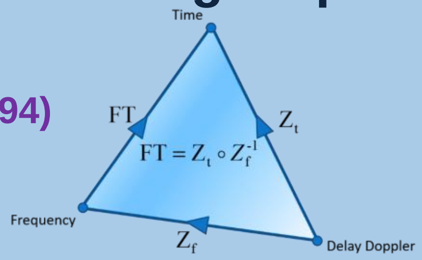
Emboli vs artifact

Solid emboli vs gaseous emboli

Solid emboli vs gaseous emboli vs artifact

Emboli classification

Signal processing



Georgiadis et al. (1994)

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Machine learning

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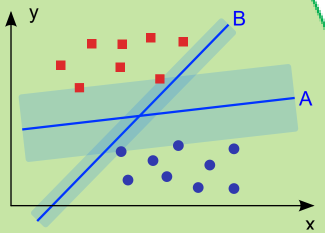

Tafsast et al. (2018)

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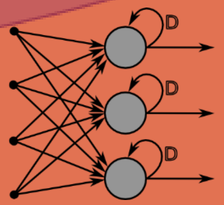


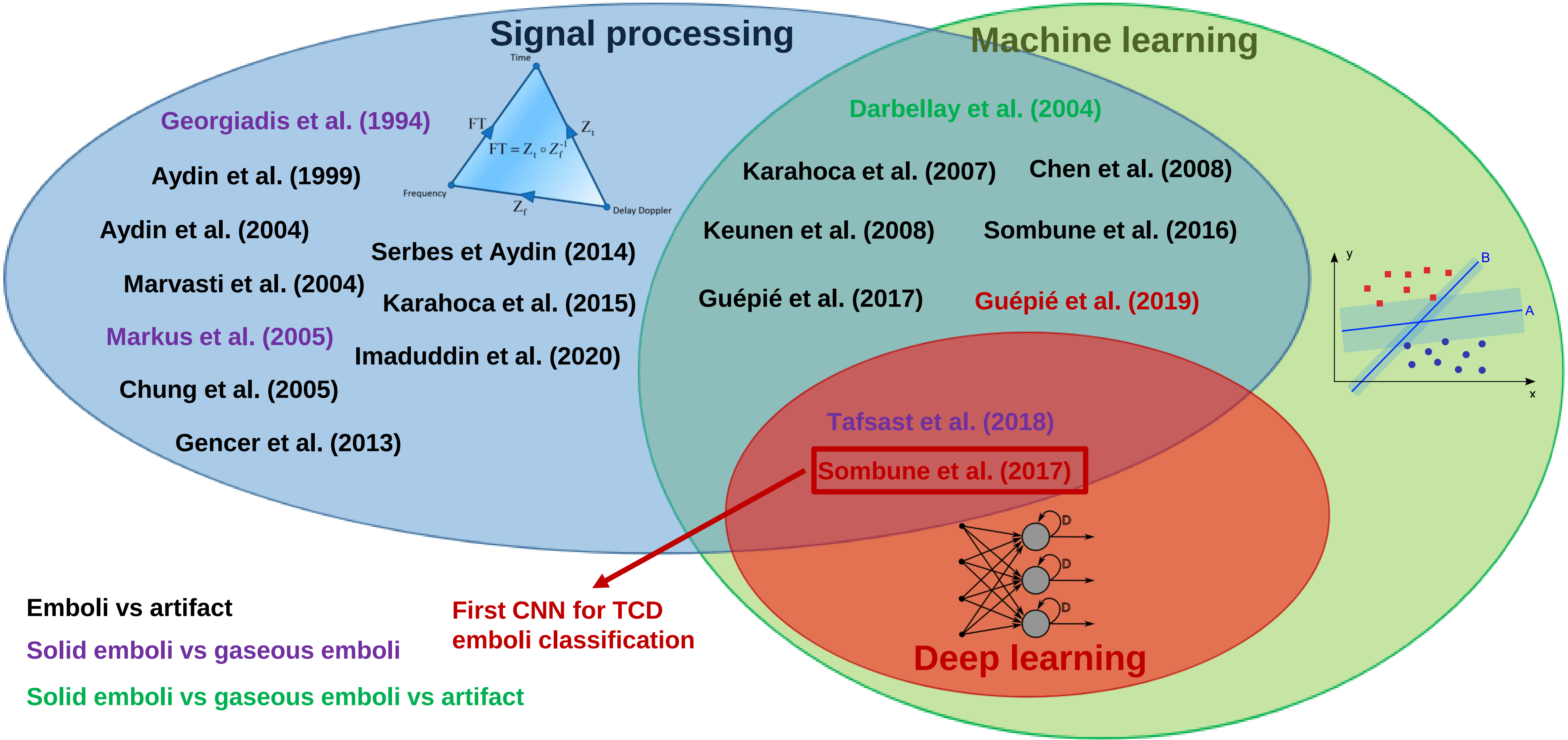
Deep learning

Emboli vs artifact

Solid emboli vs gaseous emboli

Solid emboli vs gaseous emboli vs artifact

Emboli classification



Emboli vs artifact

Solid emboli vs gaseous emboli

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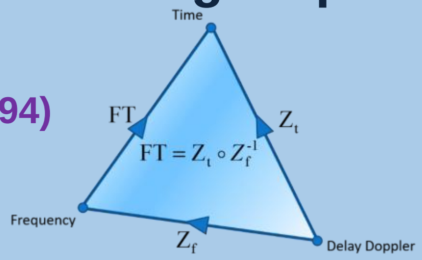
Emboli classification

State-of-the-art results on portable TCD data

Signal processing



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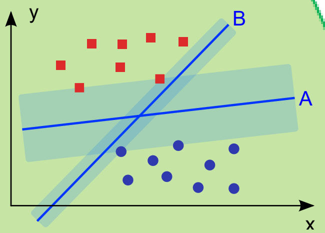

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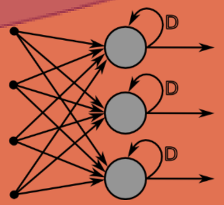


Deep learning

First CNN for TCD emboli classification

Emboli vs artifact

Solid emboli vs gaseous emboli

Solid emboli vs gaseous emboli vs artifact

Outline

Challenges: data annotation

- No public TCD emboli dataset.
- Expensive annotation (8685/68491 labeled samples).
- Annotation difficulty → Noisy labels.
- Imbalanced classes (solid emboli < 10% HITS).

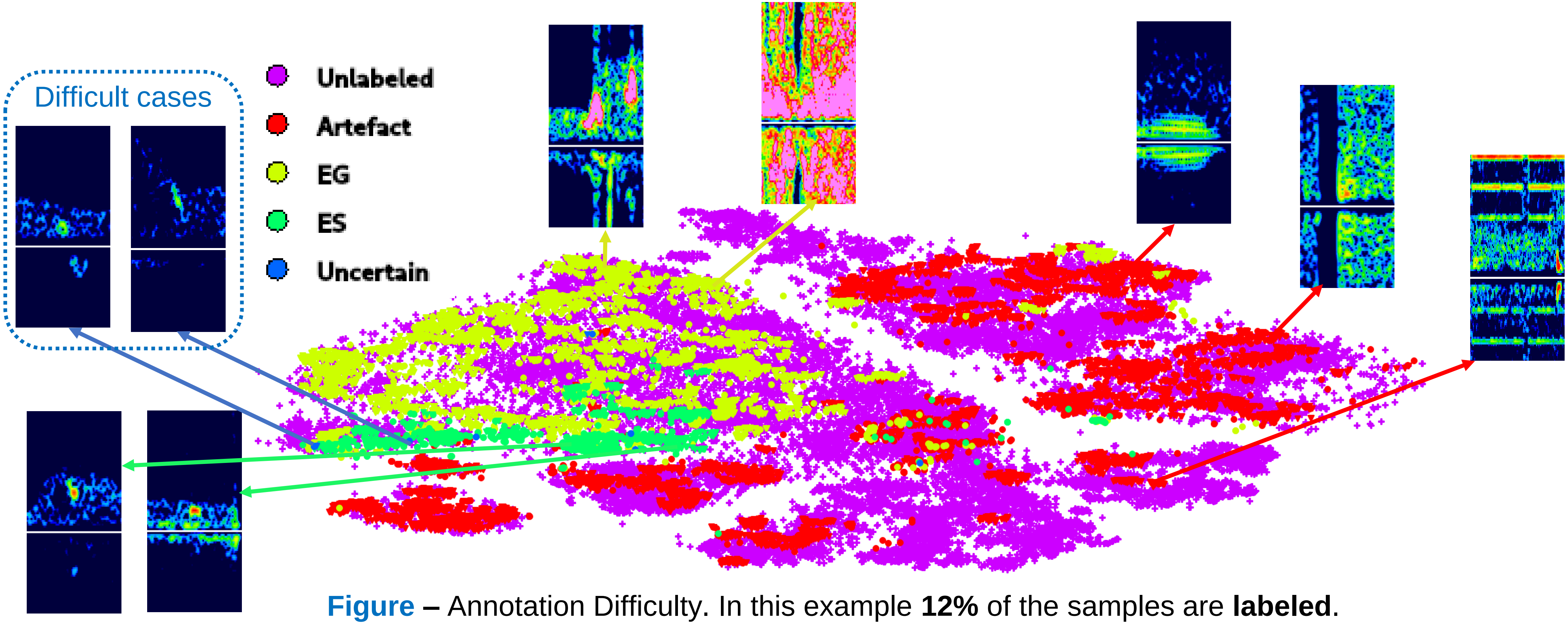
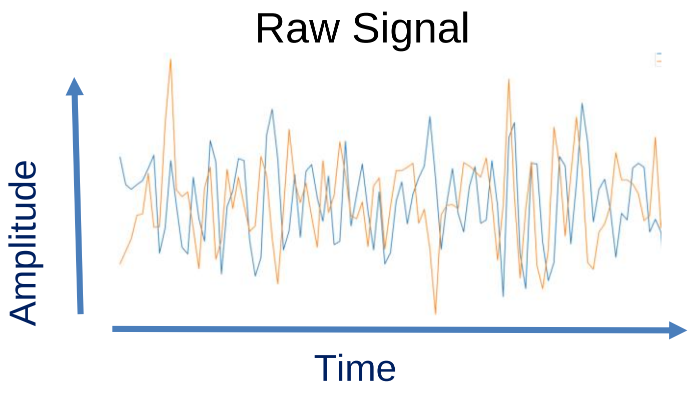


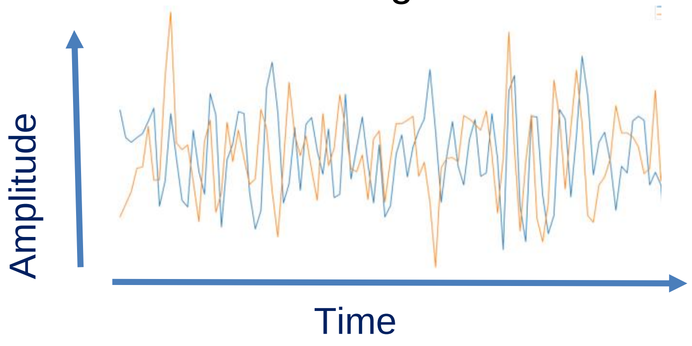
Figure – Annotation Difficulty. In this example **12%** of the samples are **labeled**.

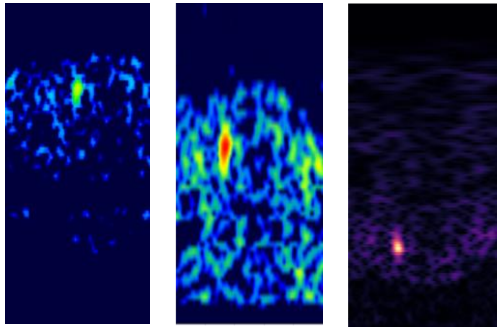
Challenges: optimal representation



Challenges: optimal representation

Raw Signal





Time-Frequency Representations
(**TFRs**)

Challenges: optimal representation

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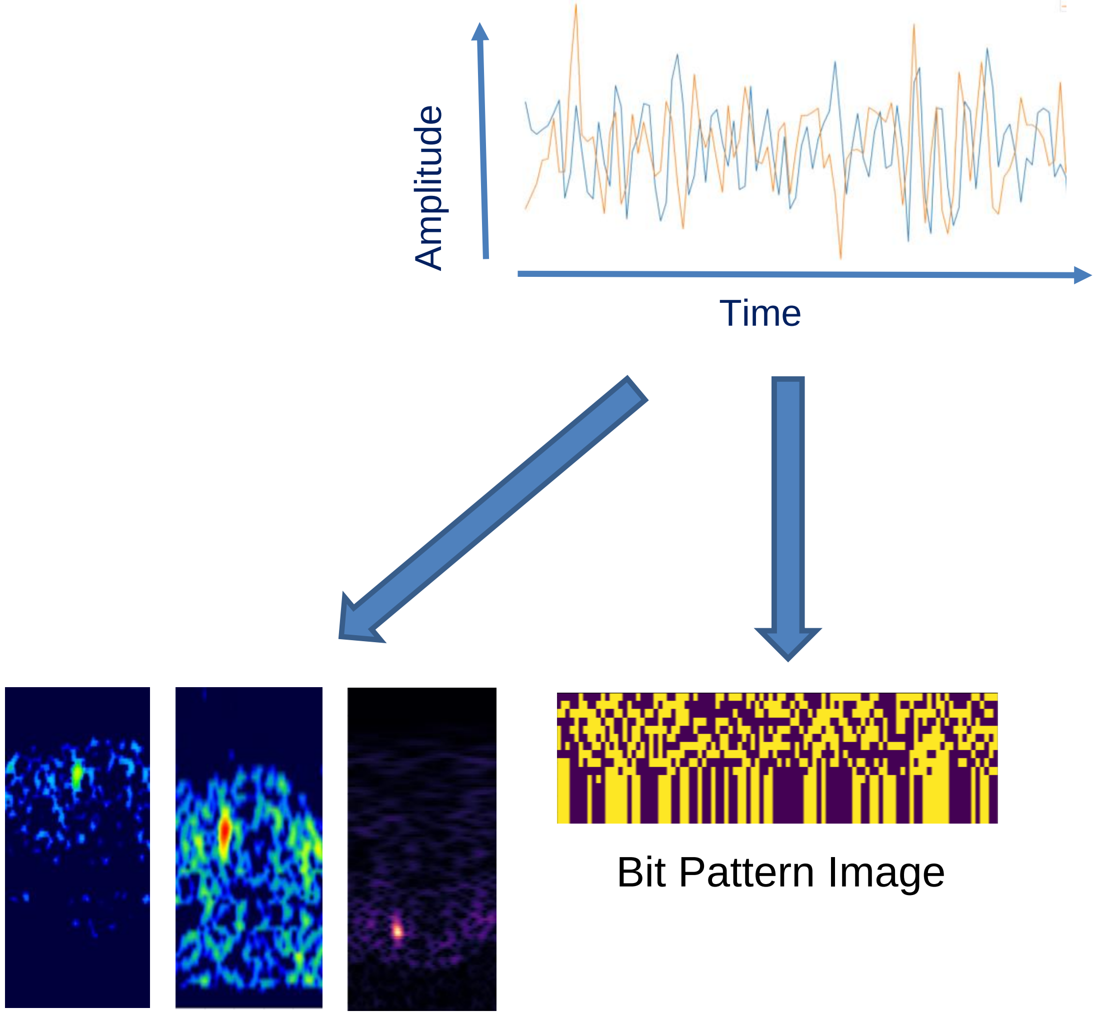

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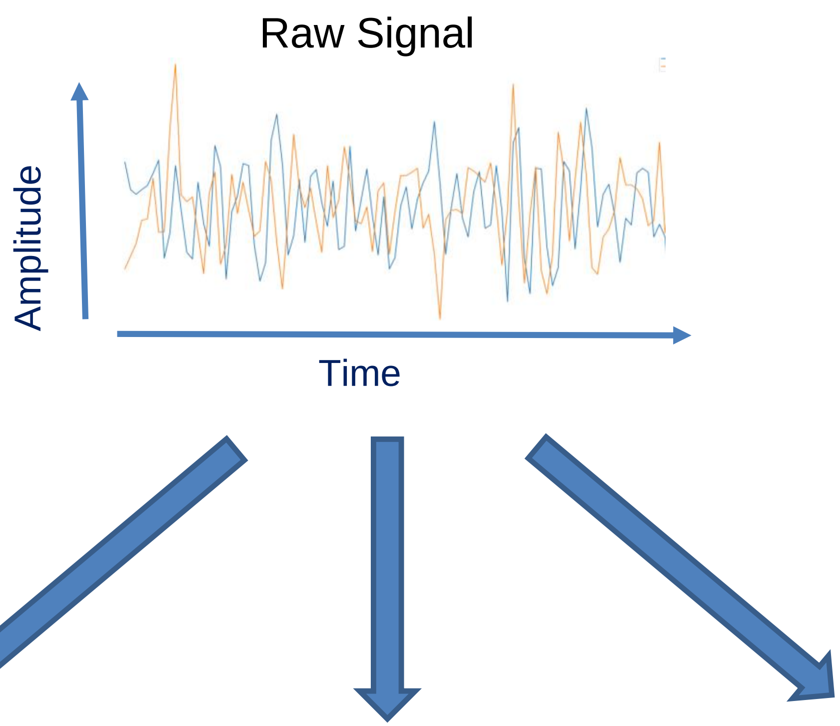

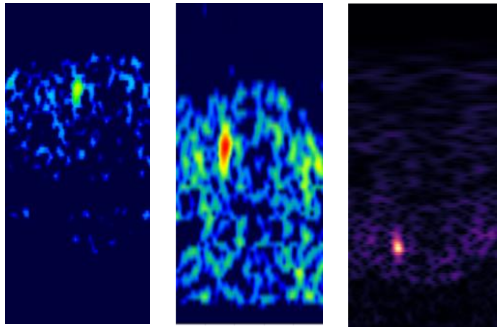

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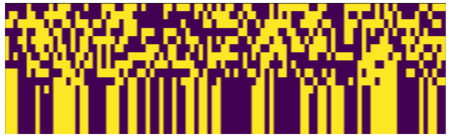
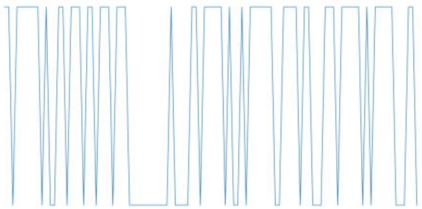
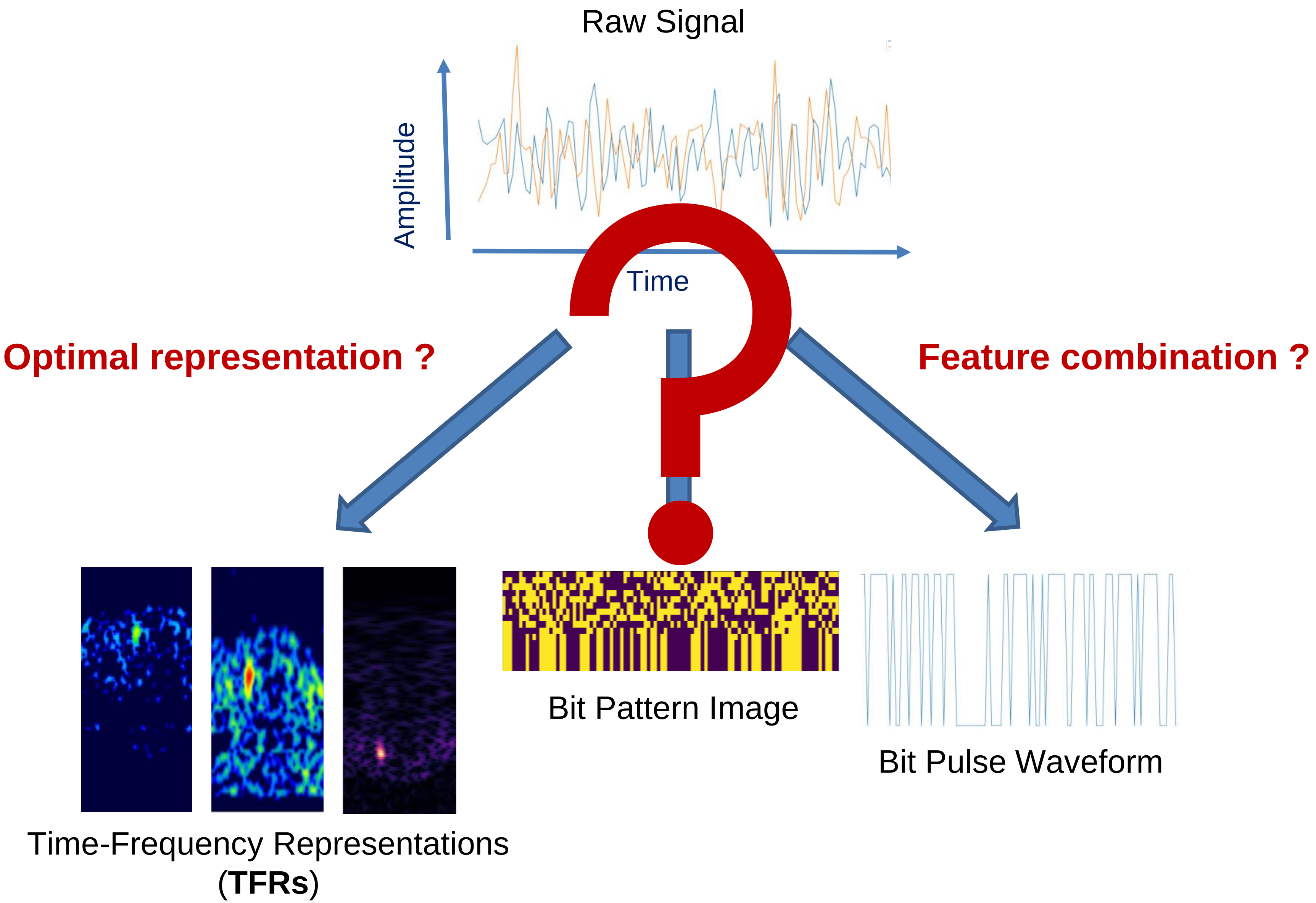


Bit Pattern Image



Bit Pulse Waveform

Challenges: optimal representation



Challenges: model compression

Figure – Portable transcranial Doppler (TCD) from Atys Medical.

Challenges: model compression

Figure – Portable transcranial Doppler (TCD) from Atys Medical.

→ Limited memory resources.

Challenges: model compression

Figure – Portable transcranial Doppler (TCD) from Atys Medical.

- Limited memory resources.
- Limited computation resources.

Challenges: model compression

Figure – Portable transcranial Doppler (TCD) from Atys Medical.

- Limited memory resources.
- Limited computation resources.
- Energy constraints.

Challenges: model compression

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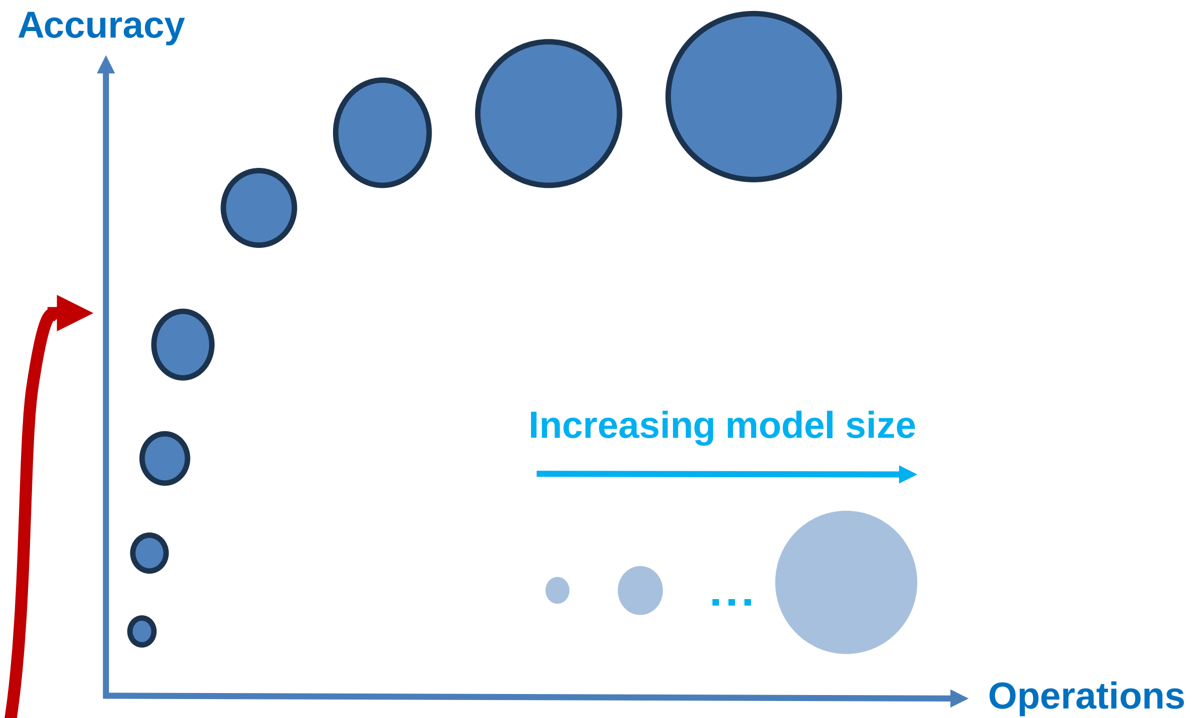

Figure – Classification accuracy based on the size and number of floating-point operations of different deep learning models (inspired from Abbas et al. 2021)

Objectives and Contributions

* Vindas et al. (IUS 2021), Vindas et al. (MEDIA 2022), Vindas et al. (IUS 2023)
** Vindas et al. (MLHC 2022), Vindas et al. (IABM 2023), Vindas et al. (EUSIPCO 2023), and Vindas et al. (Pattern Recognition 2023)

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- Semi-supervised data annotation*
- Soft labelling (annotation)*

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Objectives and Contributions

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Multiple representations

* Vindas et al. (IUS 2021), Vindas et al. (MEDIA 2022), Vindas et al. (IUS 2023)
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Objectives and Contributions

Dataset creation and annotation →

- Semi-supervised data annotation*
- Soft labelling (annotation)*

Multiple representations →

- Different models with different inputs**
- Multi-feature models

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Resource hungry models

* Vindas et al. (IUS 2021), Vindas et al. (MEDIA 2022), Vindas et al. (IUS 2023)
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Resource hungry models →

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- Model compression
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Outline

Semi-automatic data annotation based on feature space projection

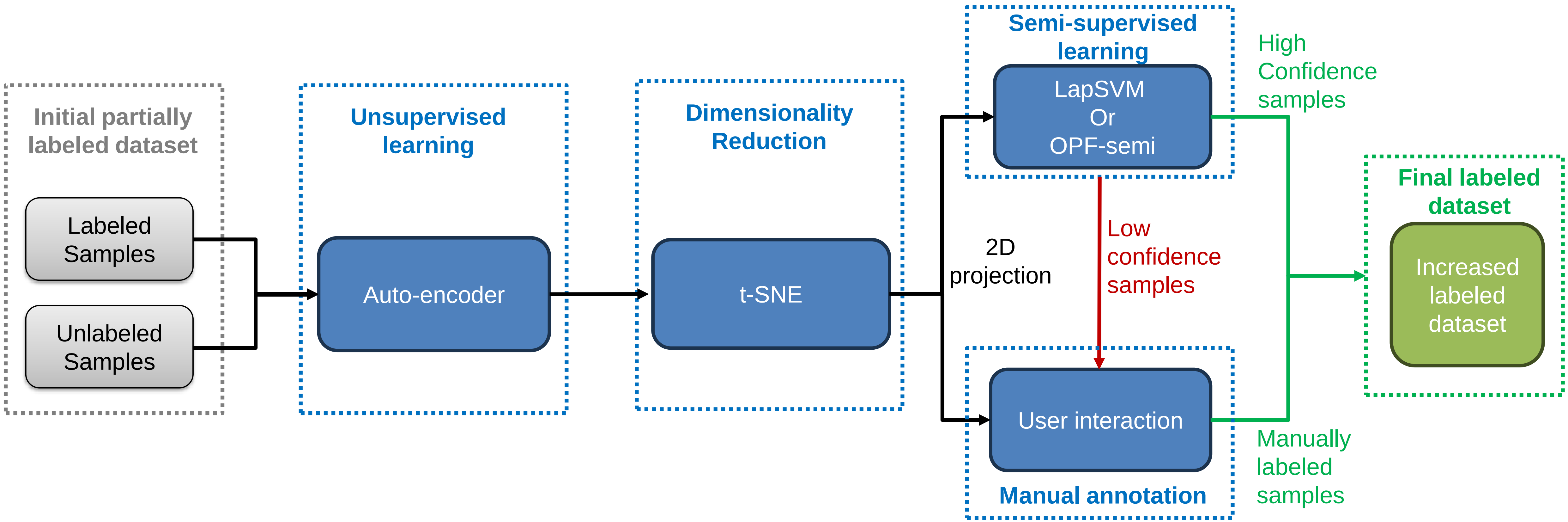
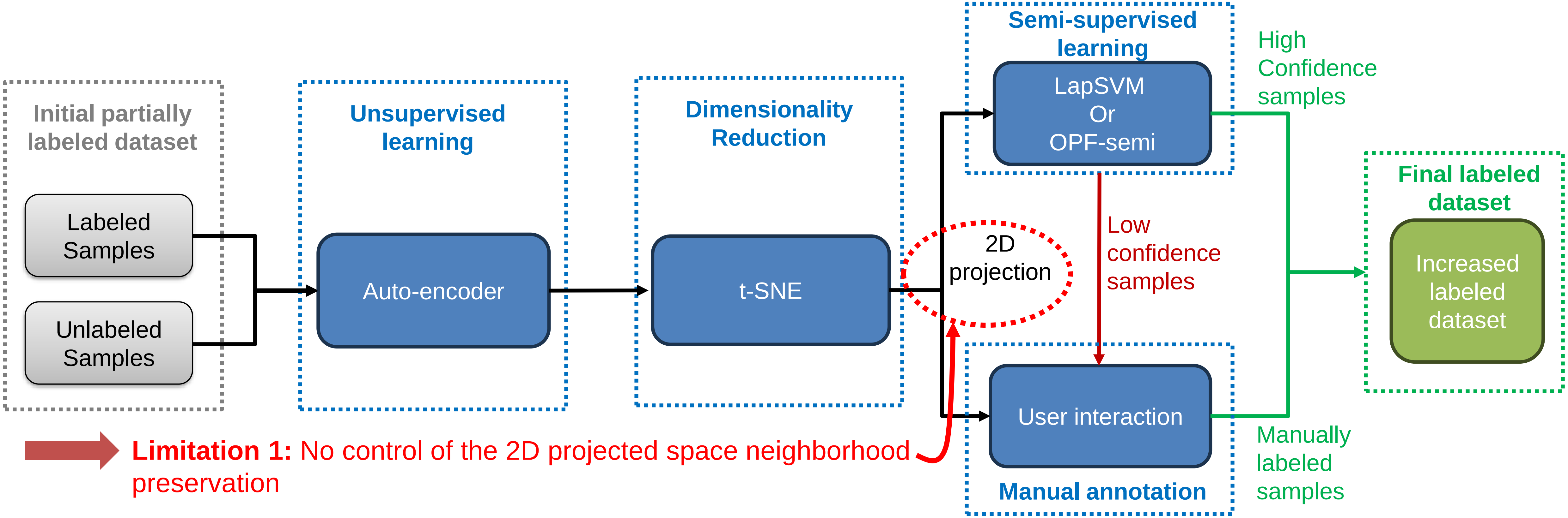


Figure – Semi-automatic data annotation based on feature space projection (**Benato et al., 2021**)

Semi-automatic data annotation based on feature space projection



Limitation 1: No control of the 2D projected space neighborhood preservation

Figure – Semi-automatic data annotation based on feature space projection (**Benato et al., 2021**)

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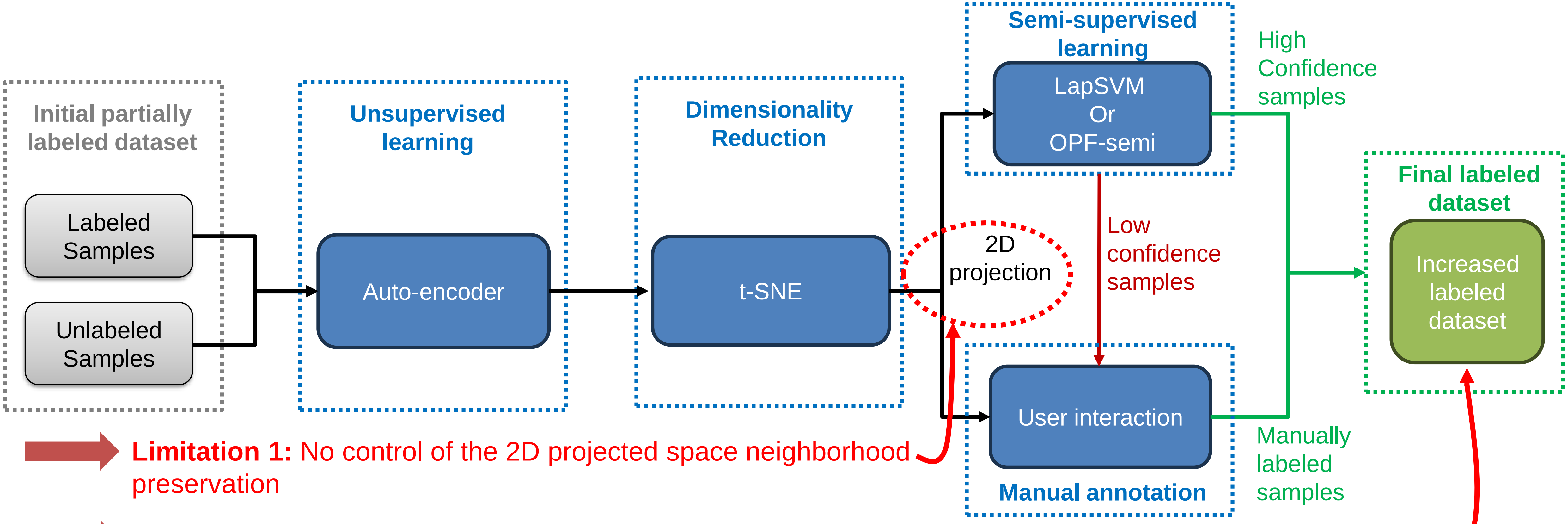

Limitation 1: No control of the 2D projected space neighborhood preservation

Limitation 2: Not taking into account introduced noise in the labels for classification

Figure – Semi-automatic data annotation based on feature space projection (**Benato et al., 2021**)

Possible solution 2D projection quality

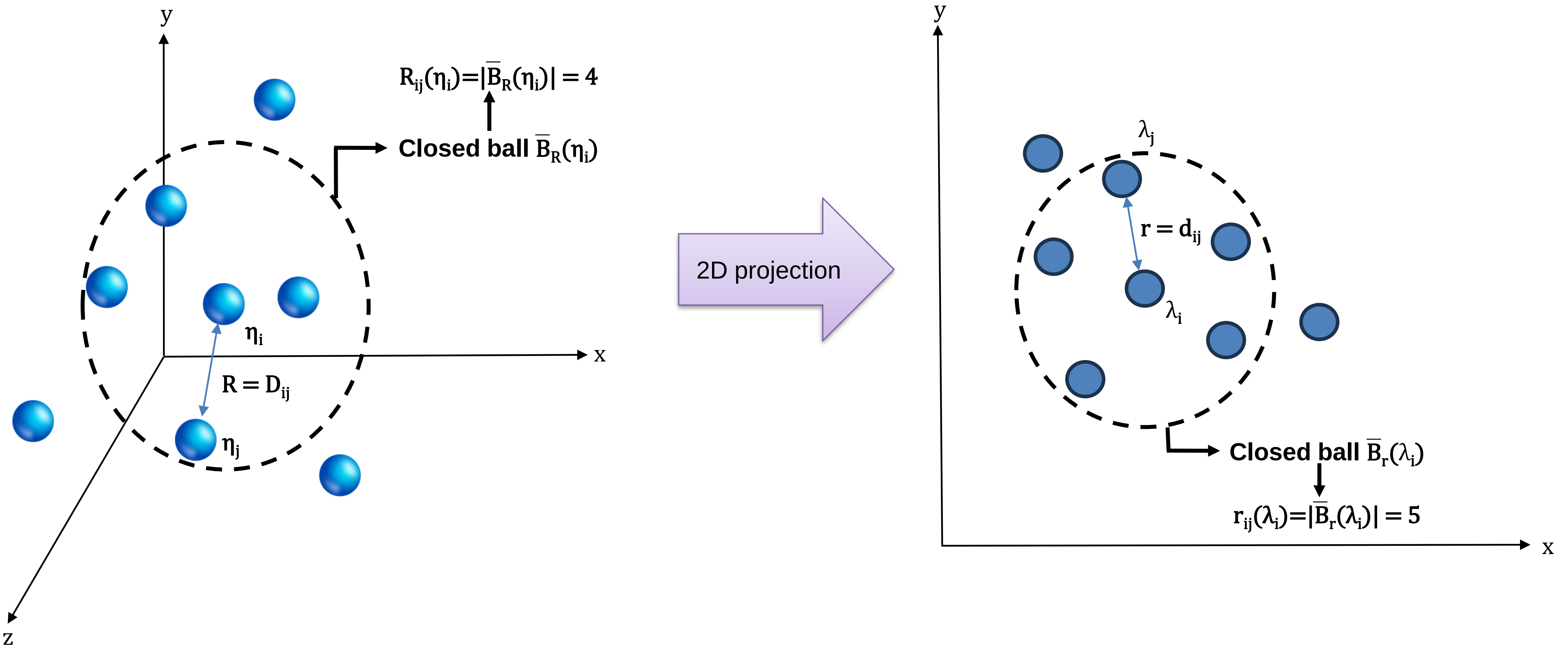

Figure – Ranks definitions during space projection (**Lueks et al., 2011**).

Possible solution to noisy-labels

Robust loss functions

Possible solution to noisy-labels

Robust loss functions

Flexible

Possible solution to noisy-labels

Robust loss functions

Flexible

Full exploration of the data

Possible solution to noisy-labels

Robust loss functions

- **Flexible**
- **Full exploration of the data**
- **No clean supervision**

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Generalized Cross Entropy Loss*

*Zhilu Zhang, Mert R. Sabuncu: Generalized Cross Entropy Loss for Training Deep Neural Networks with Noisy Labels. NeurIPS 2018: 8792-8802

Possible solution to noisy-labels

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Generalized Cross Entropy Loss*

Input sample

classes

One-hot label

Model

k^th element

$$\mathcal{L}_{GCE}(f(X), \overline{y}) = \sum_{k=1}^{K} \frac{\overline{y}_k - f_k(X)^q}{q}$$

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$$\mathcal{L}_{GCE}(f(X),\overline{y}) = \sum_{k=1}^{K} \frac{\overline{y}_k - f_k(X)^q}{q}$$

$$\xrightarrow{q \to 0} \mathcal{L}_{CE}(f(X),\overline{y})$$

Noise sensitive ✗

Fast convergence ✓

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Possible solution to noisy-labels

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Generalized Cross Entropy Loss*

Controls the trade-off between noise tolerance and convergence speed

Input sample # classes

Model One-hot label kth element

$$\mathcal{L}_{GCE}(f(X),\overline{y}) = \sum_{k=1}^{K} \frac{\overline{y}_k - f_k(X)^q}{q}$$

$q \to 0$: $\mathcal{L}_{CE}(f(X),\overline{y})$ — Noise sensitive ✗, Fast convergence ✓

$q \to 1$: $\mathcal{L}_{MAE}(f(X),\overline{y})$ — Noise tolerant ✓, Slow convergence ✗

*Zhilu Zhang, Mert R. Sabuncu: Generalized Cross Entropy Loss for Training Deep Neural Networks with Noisy Labels. NeurIPS 2018: 8792-8802

Outline

Claims of contribution 1

a. **Novel methodology** for **semi-automatic data annotation** based on local-quality (LQ) metrics, called **LQ-KNN**.

b. **Selection strategy** of the best **projection** obtained by a dimensionality reduction technique.

c. **Use robust loss** functions to improve the classification performances of a **classifier trained** on a **noisy** semi-automatic labeled **dataset**.

Proposed pipeline

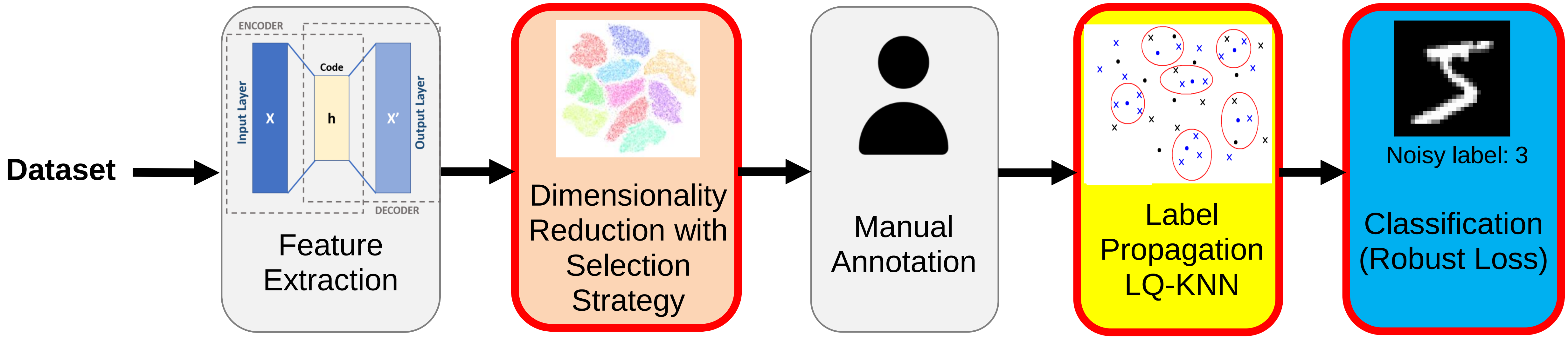


FIGURE - Semi-Automatic Data Annotation Method

Proposed pipeline

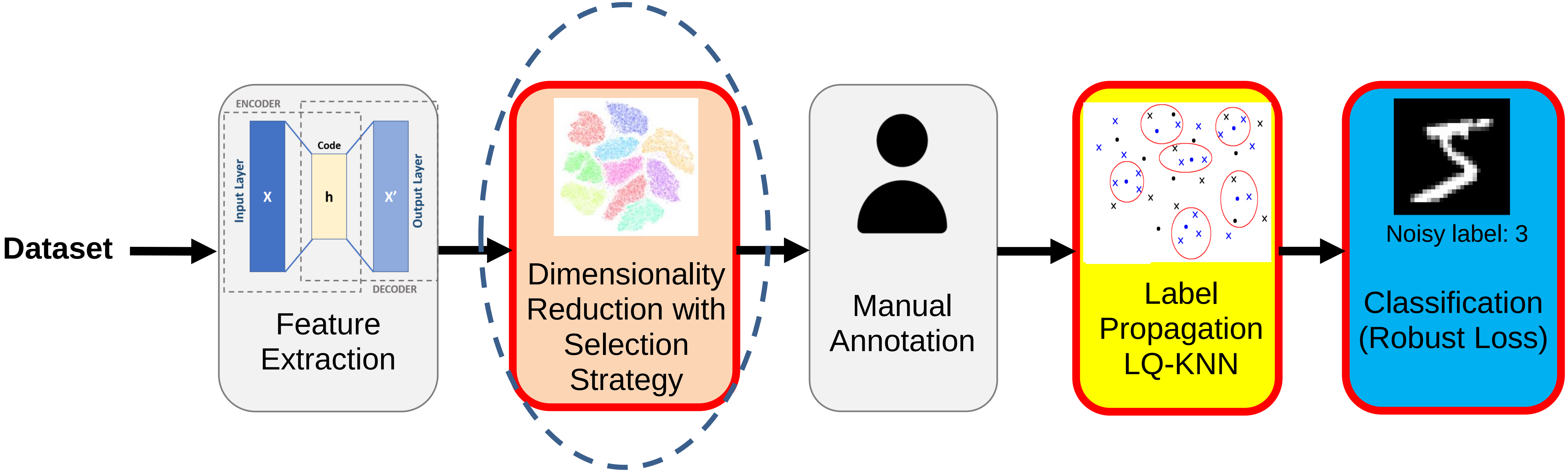
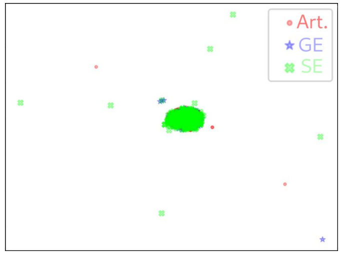
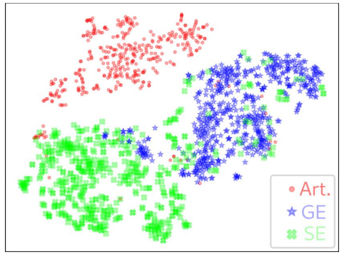


FIGURE - Semi-Automatic Data Annotation Method

Dimensionality Reduction

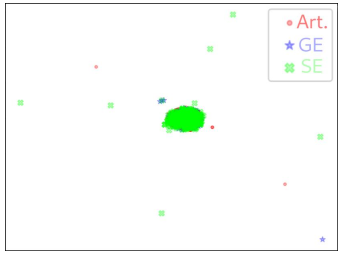


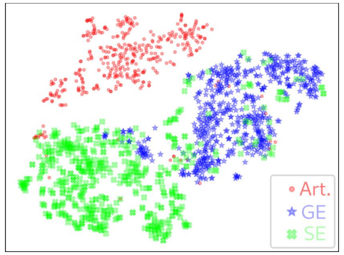
⋮



Different computed
2D projections

Dimensionality Reduction

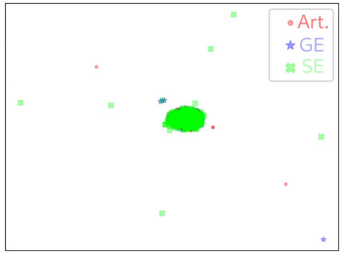




Different computed 2D projections

Silhouette Score
S computation

S = -0.56



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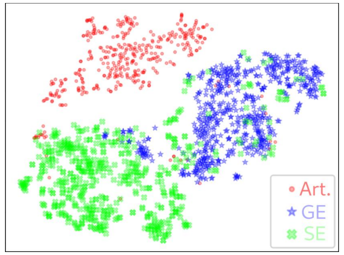
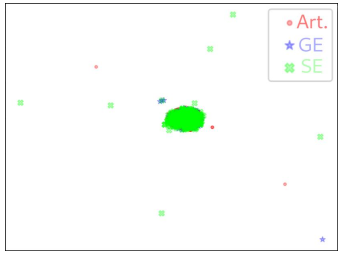


Silhouette score
$S \in [-1,1]$

Dimensionality Reduction



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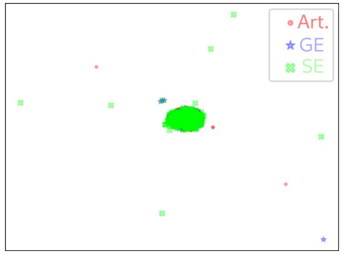

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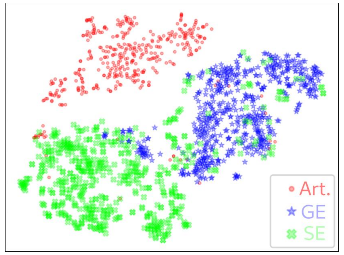

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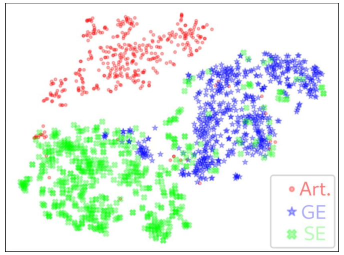
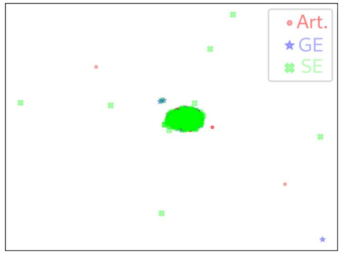


Different computed
2D projections

Silhouette score
$S \in [-1, 1]$ Distant and compact clusters

Dimensionality Reduction



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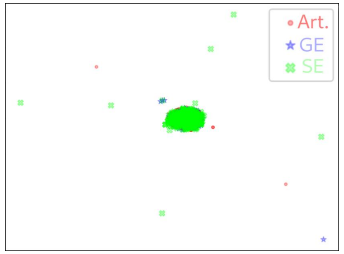

Silhouette Score
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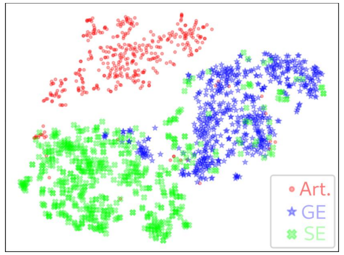

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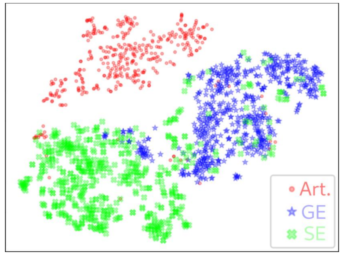
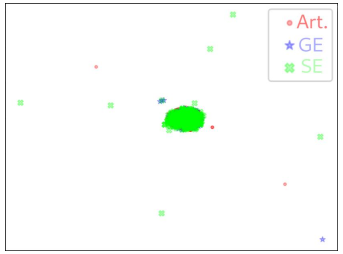


Different computed
2D projections

Silhouette score
$S \in [-1, 1]$

Overlapping clusters

Dimensionality Reduction



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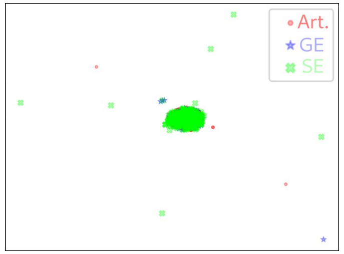
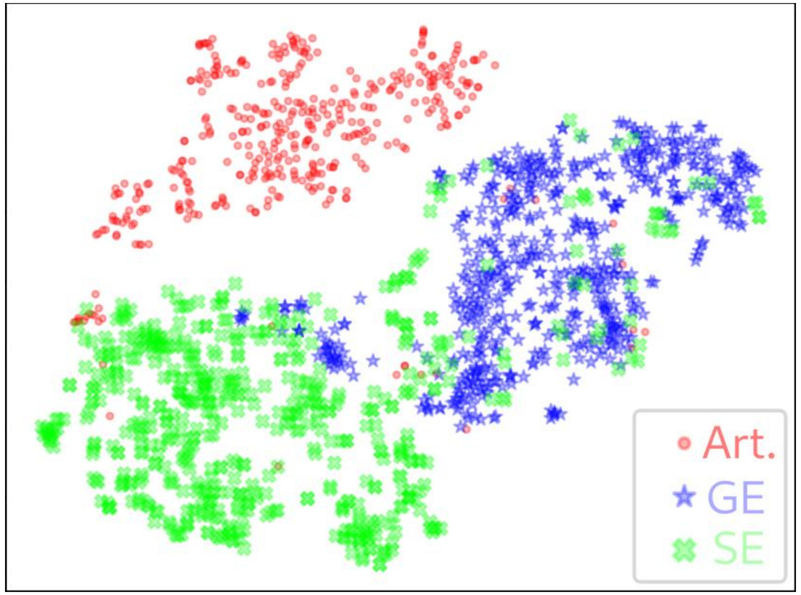
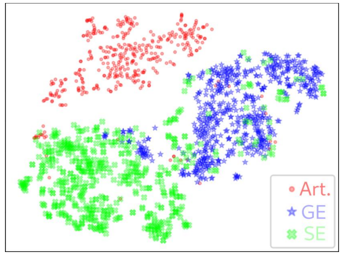


Silhouette Score
S computation

Best Silhouette
Score

S = 0.49





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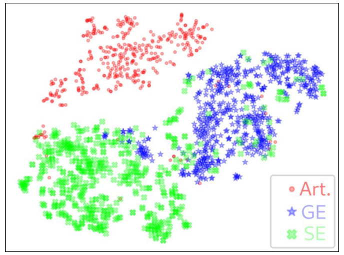

Selected projection for manual annotation and label propagation

Different computed 2D projections

Silhouette score
$S \in [-1,1]$

Proposed pipeline

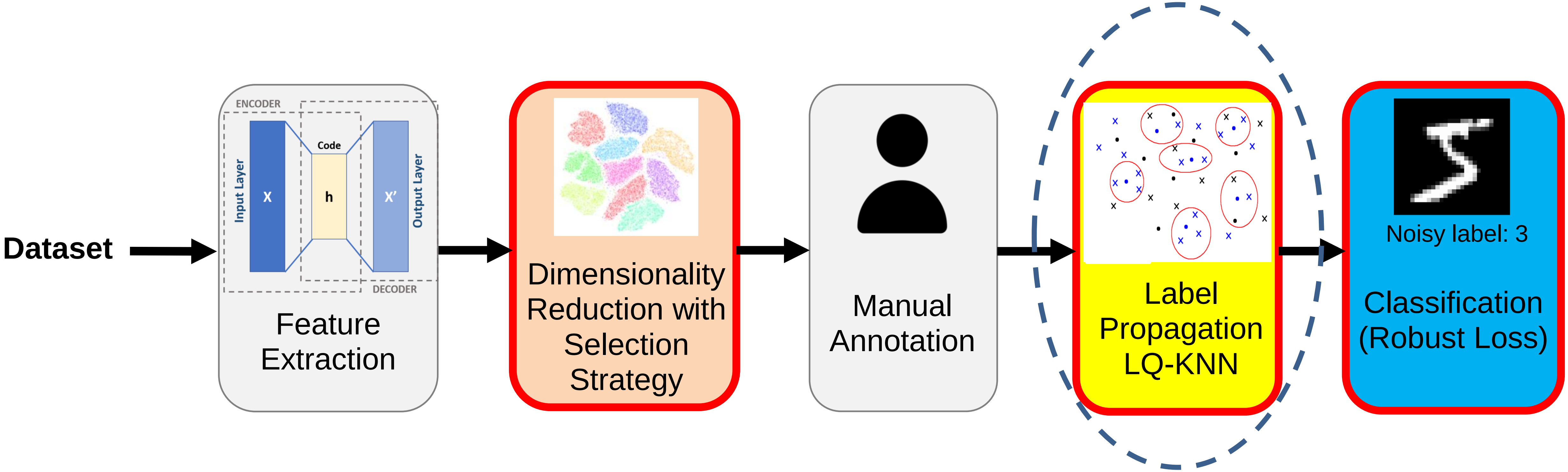

FIGURE - Semi-Automatic Data Annotation Method

Semi-automatic label propagation: Assumptions

- Based on a **K-nearest neighbors** (**KNN**) approach.
- **Three assumptions**:
  - Structure/cluster assumption[1].
  - Local structure preservation.
  - Annotation space coverage.

[1] Olivier Chapelle, Bernhard Schölkopf, and Alexander Zien, eds.Semi-supervised learning. Adaptive computation and machine learning. OCLC: ocm64898359. Cambridge, Mass: MIT Press, 2006. 508 pp.isbn: 978-0-262-03358-9

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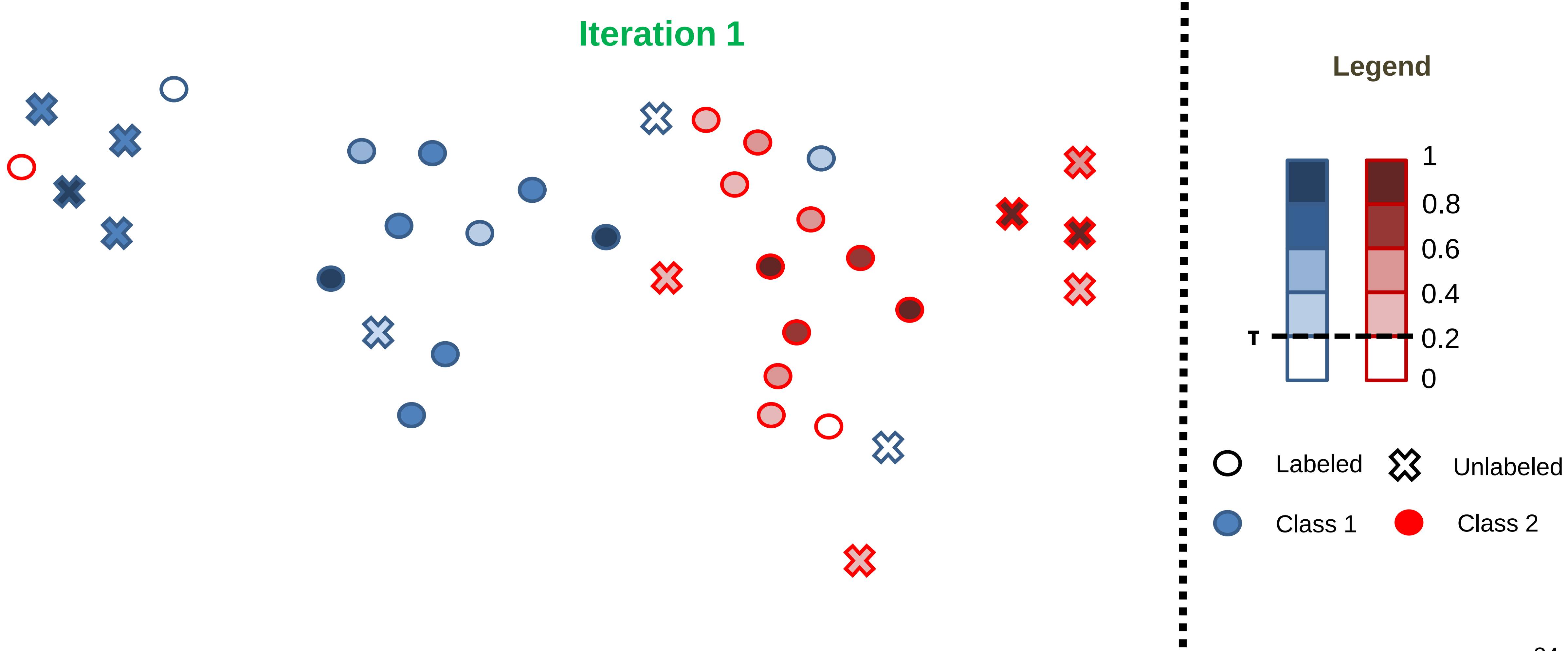
Local quality (**LQ**) K-nearest neighbor (**KNN**) label propagation : **LQ-KNN**

[1] Olivier Chapelle, Bernhard Schölkopf, and Alexander Zien, eds.Semi-supervised learning. Adaptive computation and machine learning. OCLC: ocm64898359. Cambridge, Mass: MIT Press, 2006. 508 pp.isbn: 978-0-262-03358-9

Semi-automatic label propagation LQ-KNN

Figure – Example with two neighbors (i.e. **K = 2** and **τ = 0.2**).

Semi-automatic label propagation LQ-KNN



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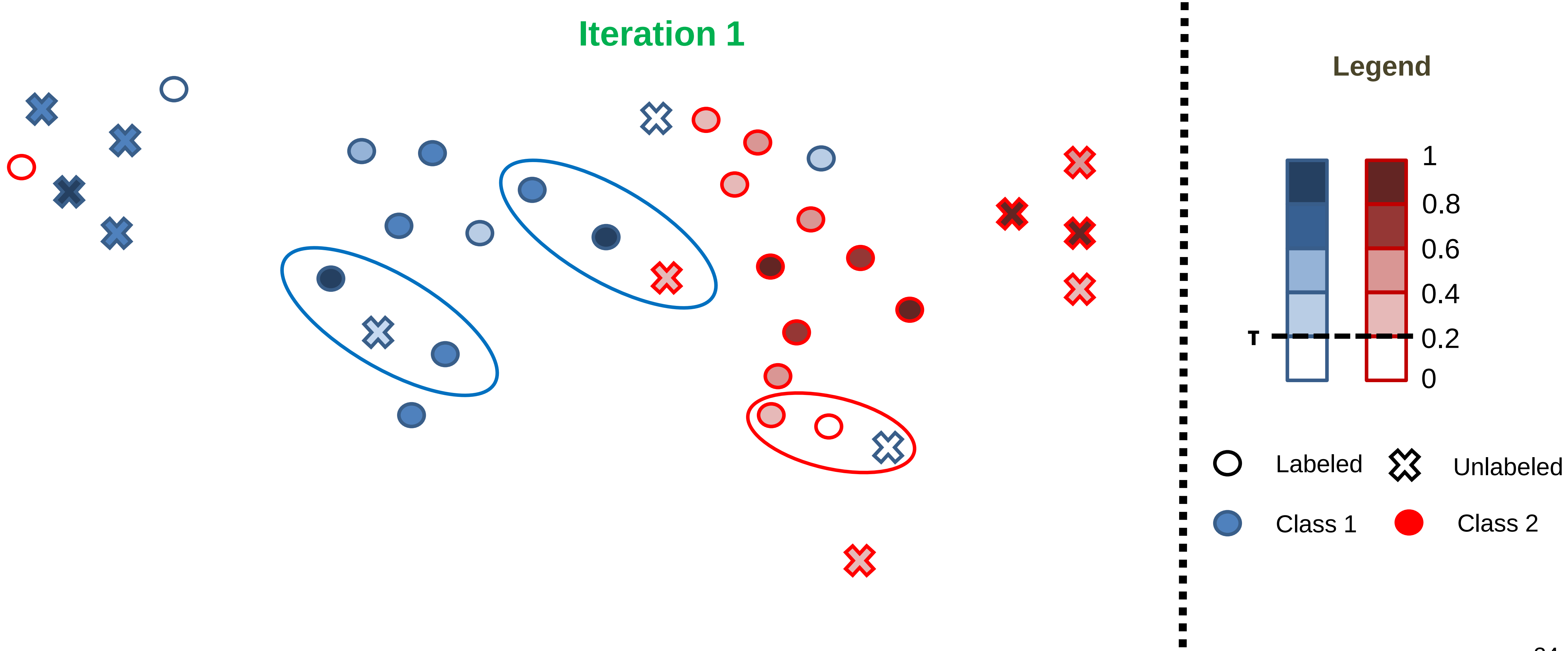

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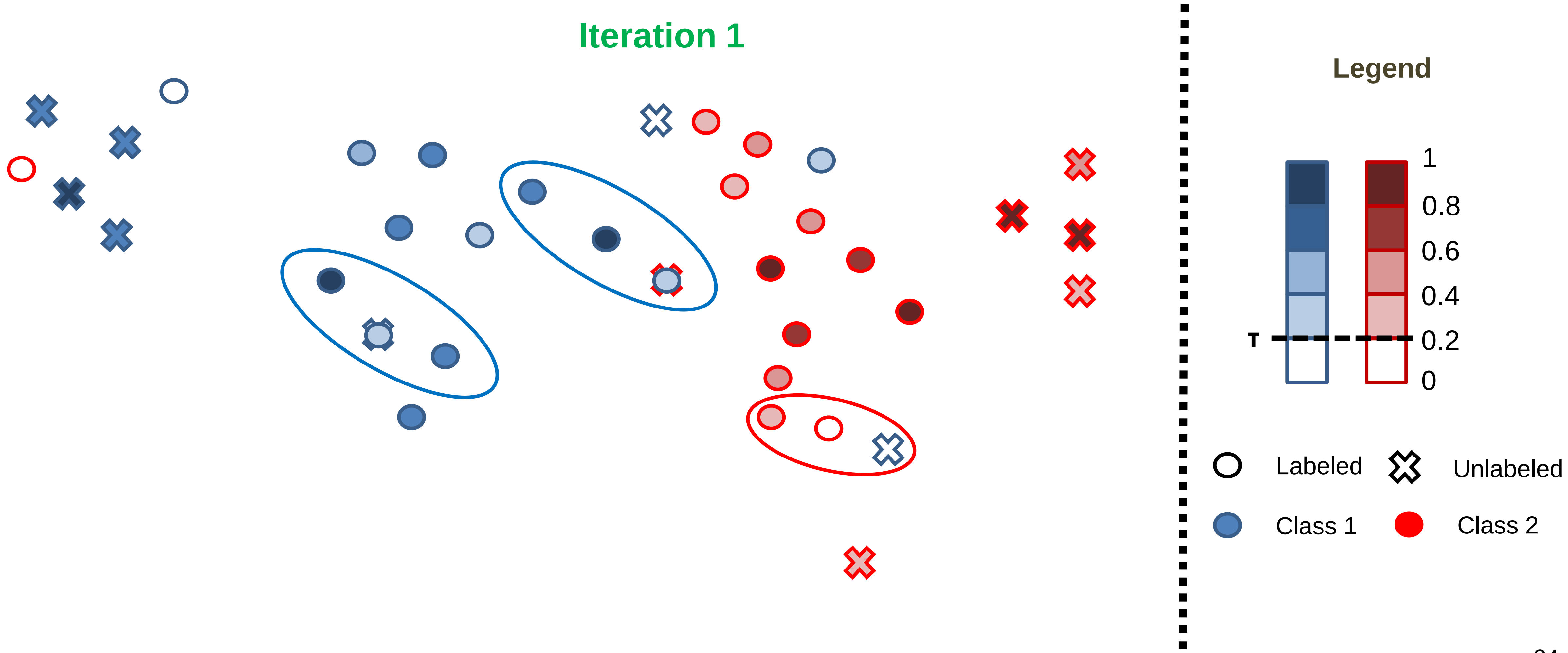

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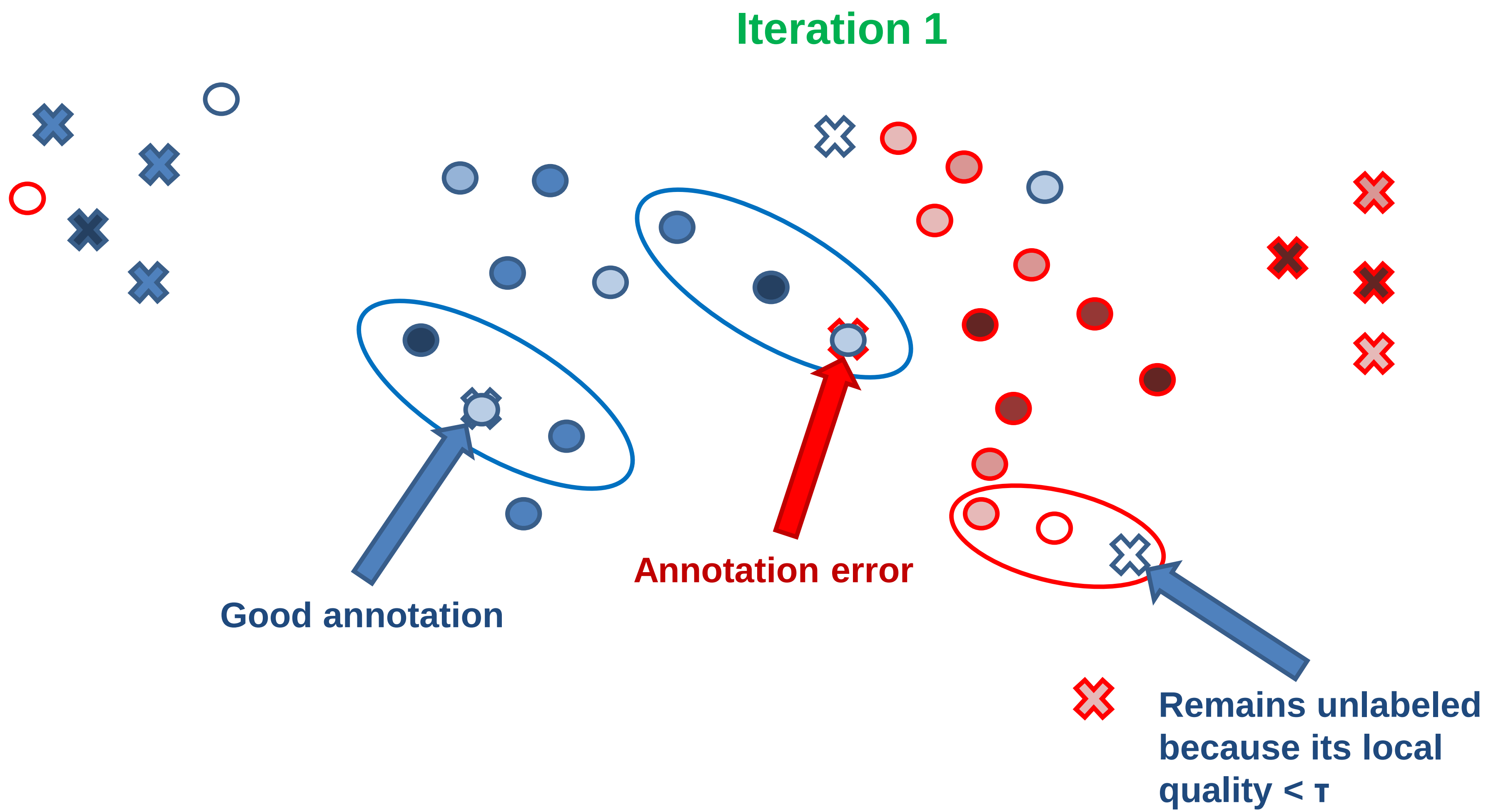

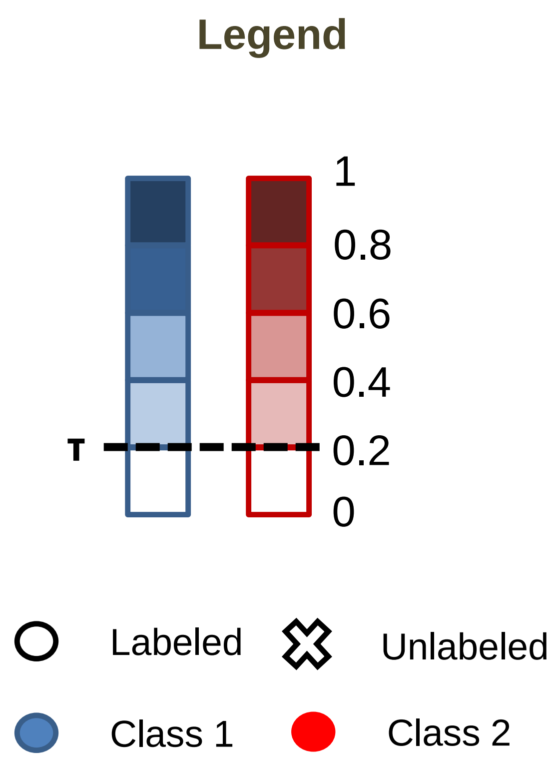

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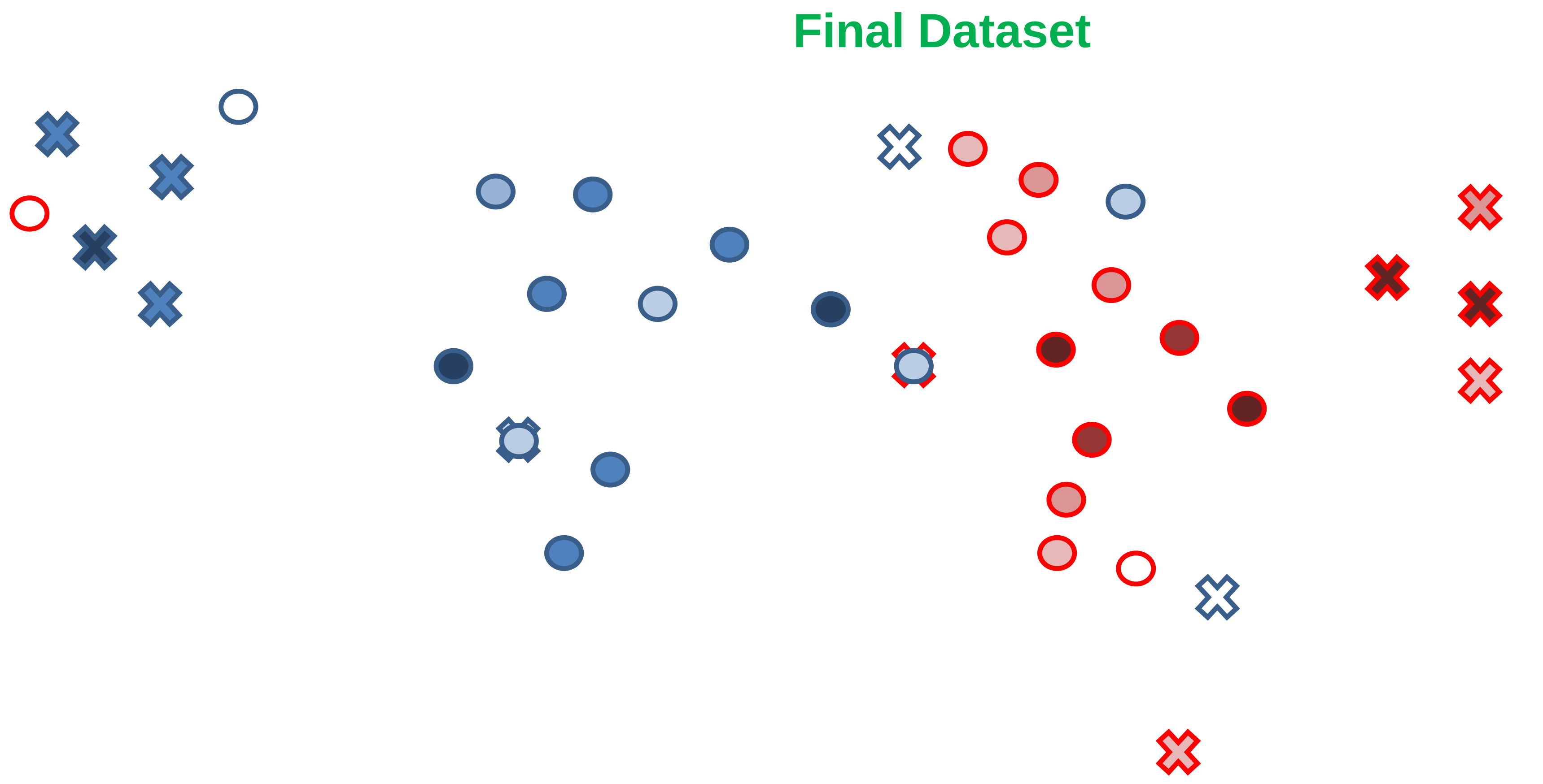

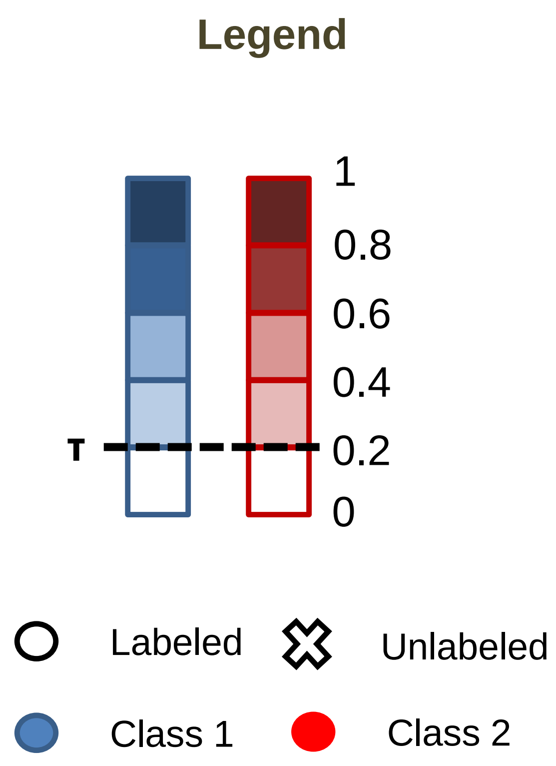

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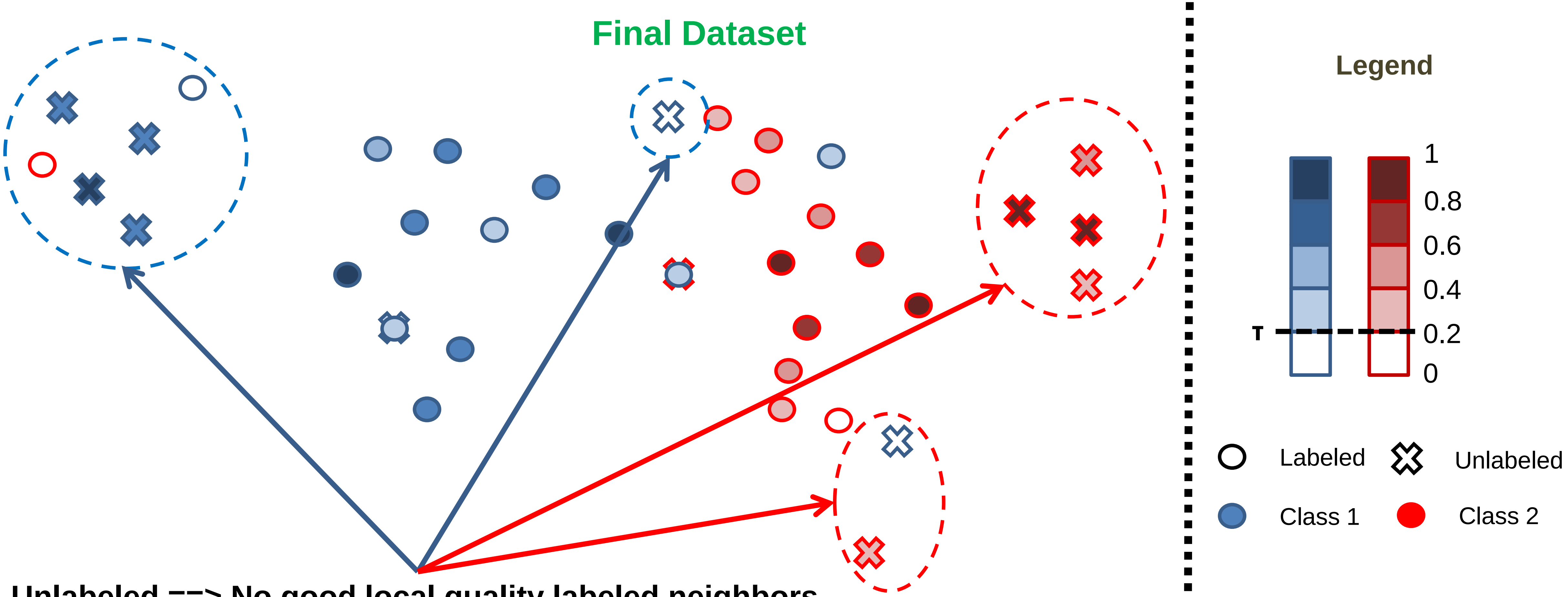

Unlabeled ==> No good local quality labeled neighbors

Figure – Example with two neighbors (i.e. **K = 2** and **τ = 0.2**).

Outline

Proposed pipeline

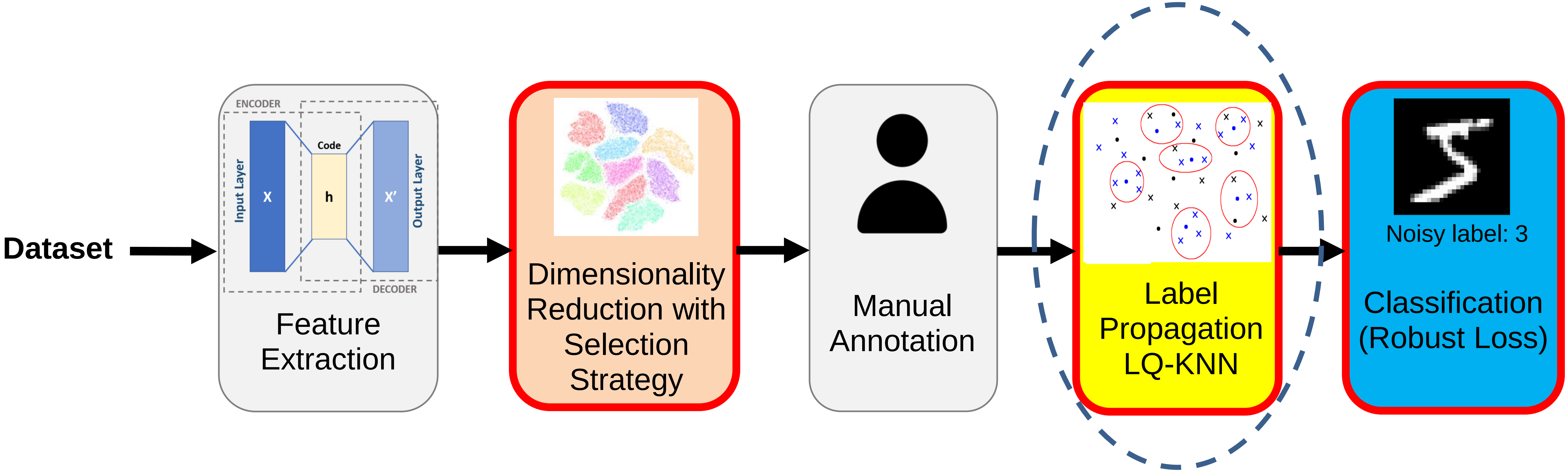

FIGURE - Semi-Automatic Data Annotation Method

Contribution 1.a.: Semi-automatic data annotation method **state-of-the-art comparison**

Dataset	Prop. Method	$\lvert\mathcal{L}\rvert$	$\lvert\mathcal{U}\rvert$	τ	K	Annot. acc.	Final % of labeled samples	Annotation time in ms (/sample)
OrganCMNIST	OPF-Semi	1534	13858	-	10	75.22 ± 4.48	**100 ± 0**	86.52 ± 0.51
	Std-KNN			0.1		*79.86 ± 0.67*	*99.00 ± 0.20*	**(23.41 ± 1.98) ×10^{-3}**
	LQ-KNN			-	-	**82.73 ± 0.44**	96.24 ± 1.09	*(44.36 ± 5.69)* ×10^{-3}
HITS	OPF-Semi	152	1393	-	10	78.40 ± 13.44	**100 ± 0**	9.48 ± 1.10
	Std-KNN			0.1		*81.36 ± 1.81*	*99.58 ± 0.63*	**(10.04 ± 0.18) ×10^{-3}**
	LQ-KNN				-	**82.67 ± 2.02**	98.50 ± 0.80	*(16.13 ± 0.35)* ×10^{-3}

Table – Label propagation methods comparison on different medical datasets

Contribution 1.a.: Semi-automatic data annotation method **state-of-the-art comparison**

Minimal local quality threshold

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Contribution 1.a.: Semi-automatic data annotation method **state-of-the-art comparison**

Considered neighborhood to propagate the labels

Minimal local quality threshold

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Table – Label propagation methods comparison on different medical datasets

Contribution 1.a.: Semi-automatic data annotation method **state-of-the-art comparison**

Considered neighborhood to propagate the labels

Annotation accuracy of the new labeled samples

$$\frac{\#\text{ correct new labeled samples}}{\#\text{ new labeled samples}}$$

Minimal local quality threshold

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Table – Label propagation methods comparison on different medical datasets

Contribution 1.a.: Semi-automatic data annotation method **state-of-the-art comparison**

Considered neighborhood to propagate the labels

Annotation accuracy of the new labeled samples

$$\frac{\#\text{ correct new labeled samples}}{\#\text{ new labeled samples}}$$

Minimal local quality threshold

Dataset	Prop. Method	$\lvert\mathcal{L}\rvert$	$\lvert\mathcal{U}\rvert$	τ	K	Annot. acc.	Final % of labeled samples	Annotation time in ms (/sample)
OrganCMNIST	OPF-Semi	1534	13858	-	10	75.22 ± 4.48	**100 ± 0**	86.52 ± 0.51
	Std-KNN			0.1	10	*79.86 ± 0.67*	*99.00 ± 0.20*	**(23.41 ± 1.98) ×10^{-3}**
	LQ-KNN			-	-	**82.73 ± 0.44**	96.24 ± 1.09	*(44.36 ± 5.69)* ×10^{-3}
HITS	OPF-Semi	152	1393	-	10	78.40 ± 13.44	**100 ± 0**	9.48 ± 1.10
	Std-KNN			0.1	10	*81.36 ± 1.81*	*99.58 ± 0.63*	**(10.04 ± 0.18) ×10^{-3}**
	LQ-KNN				-	**82.67 ± 2.02**	98.50 ± 0.80	*(16.13 ± 0.35)* ×10^{-3}

Table – Label propagation methods comparison on different medical datasets

Contribution 1.a.: Semi-automatic data annotation method **state-of-the-art comparison**

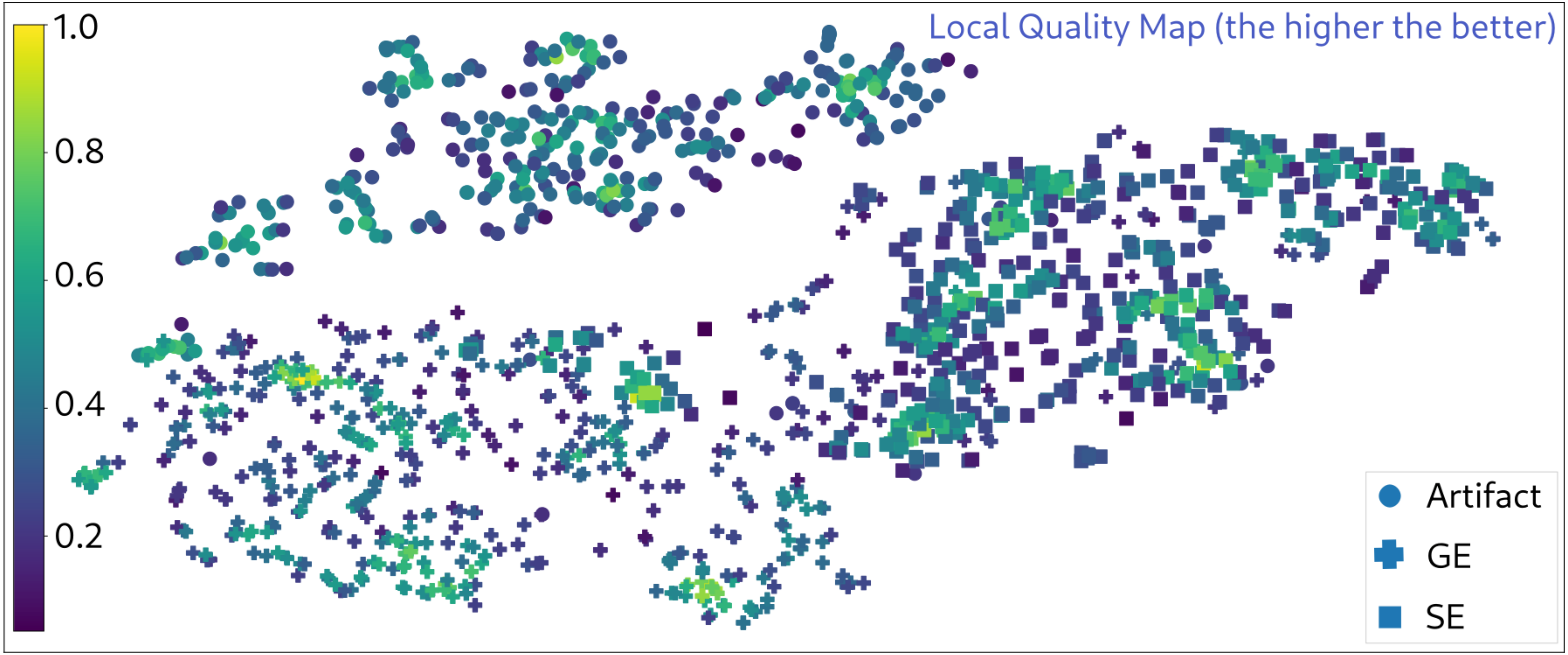


Figure - Local Quality Map of the unlabeled samples

Contribution 1.a.: Semi-automatic data annotation method **state-of-the-art comparison**

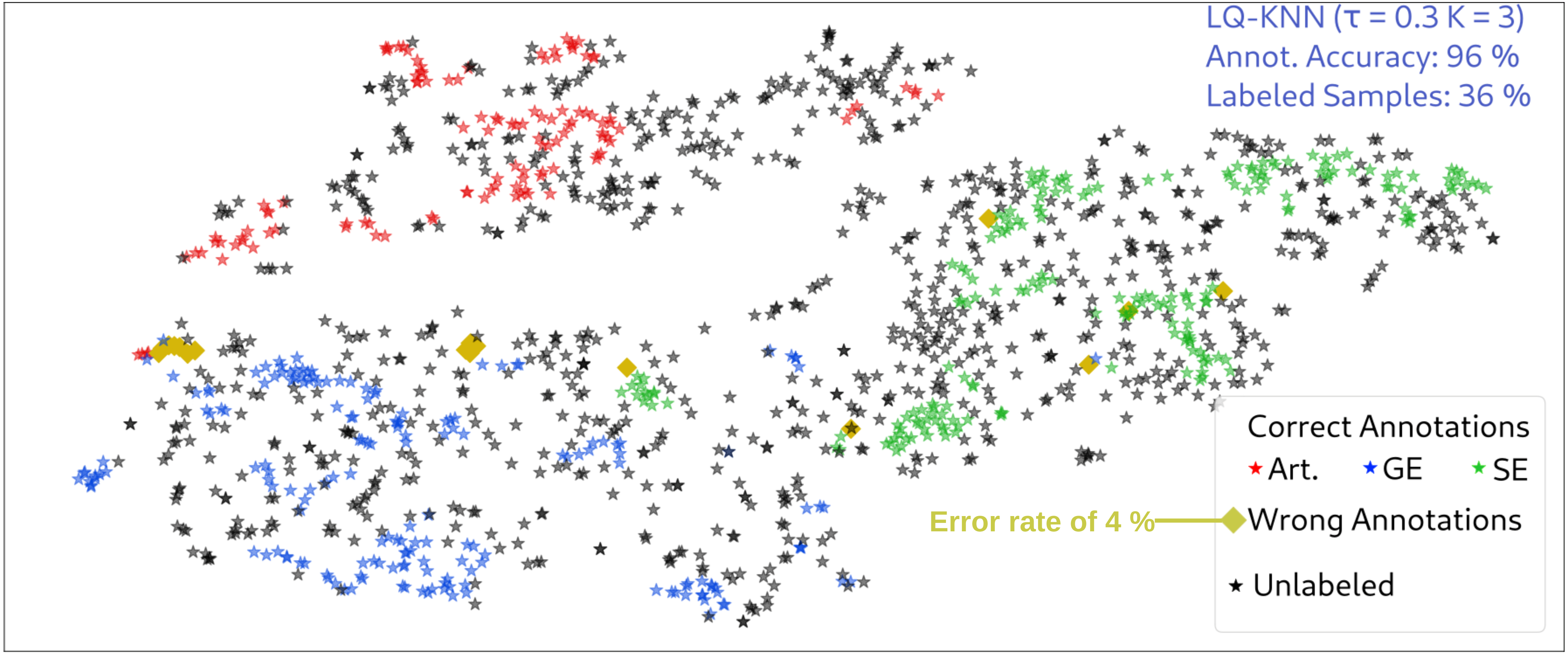


Figure - *LQ-KNN* label propagation with **K = 3** and **τ = 0.3**

Contribution 1.a.: Semi-automatic data annotation method **state-of-the-art comparison**

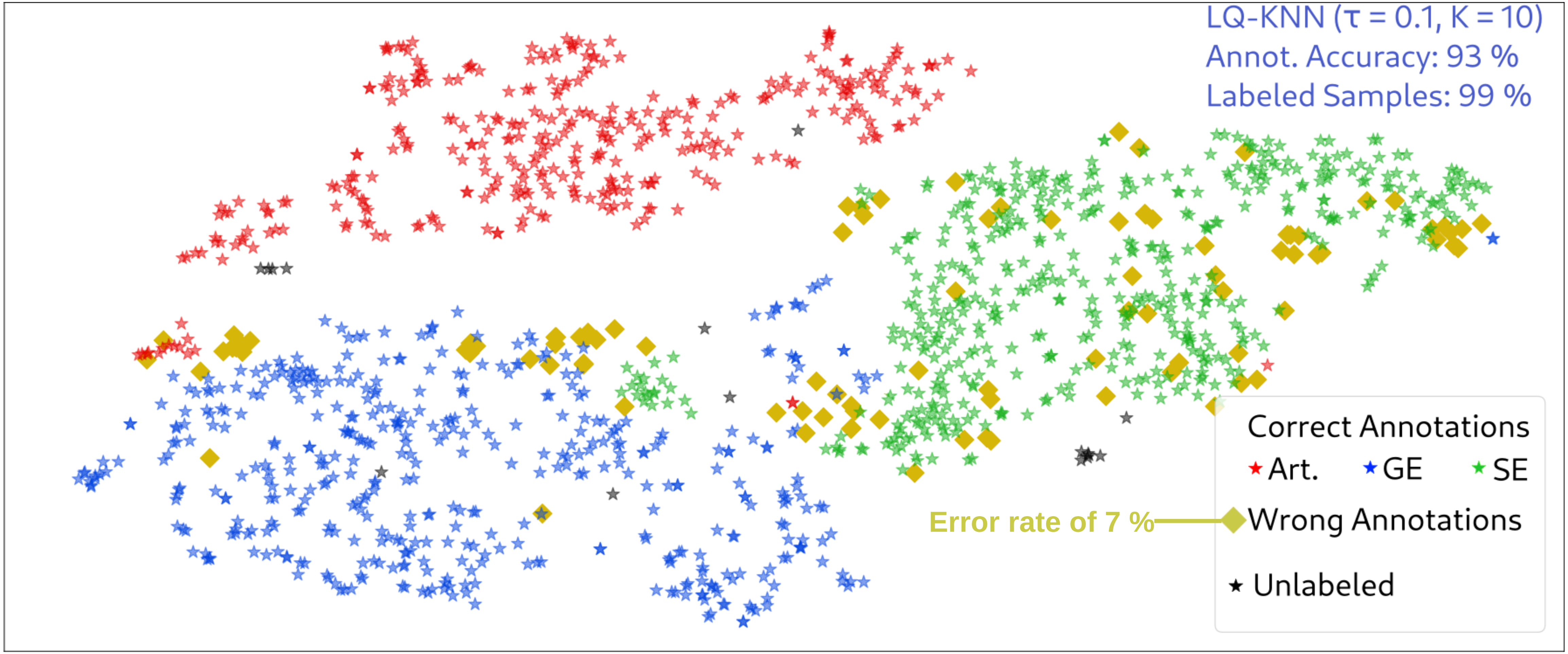


Figure - *LQ-KNN* label propagation with **K = 10** and **τ = 0.1**

Contribution 1.a.: Semi-automatic data annotation method **state-of-the-art comparison**

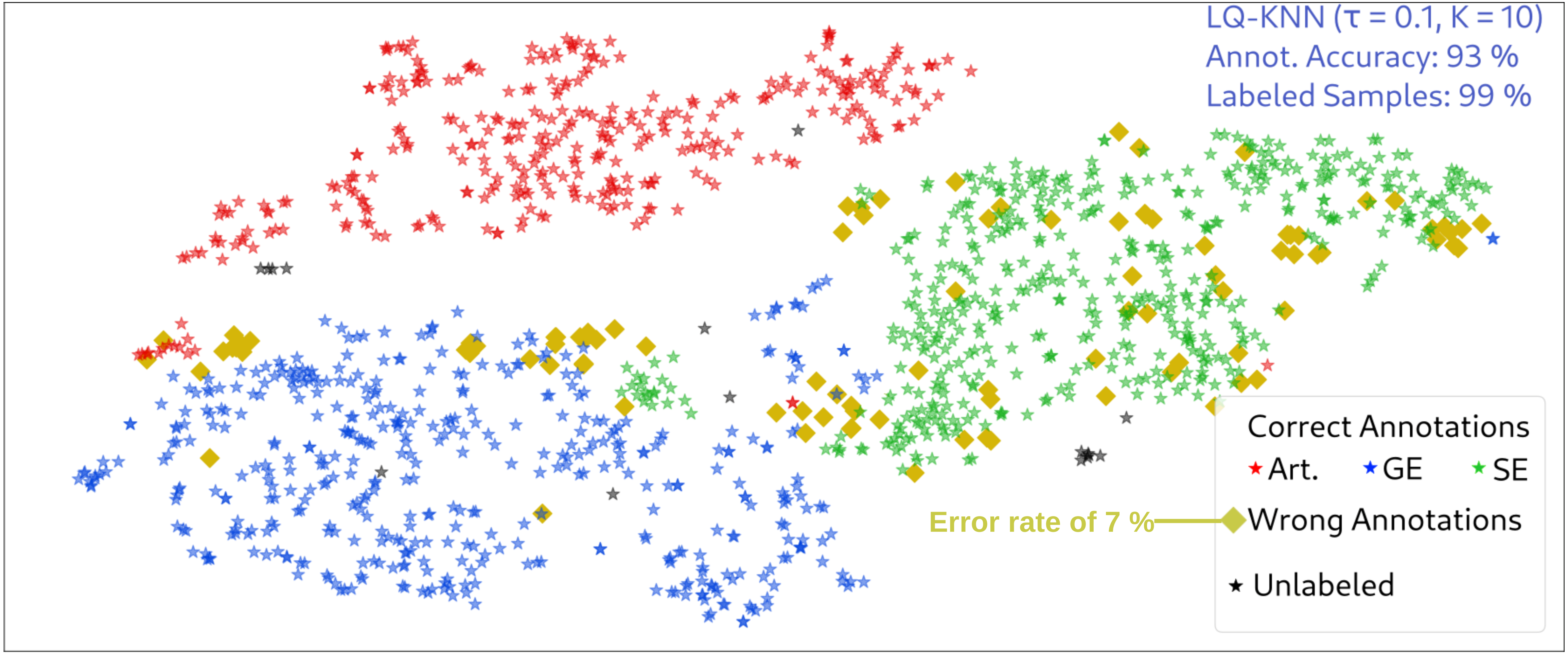


Figure - *LQ-KNN* label propagation with **K = 10** and **τ = 0.1**

K and **τ** control the **trade-off** between **annotation errors** and **quantity of labeled samples**.

Proposed pipeline

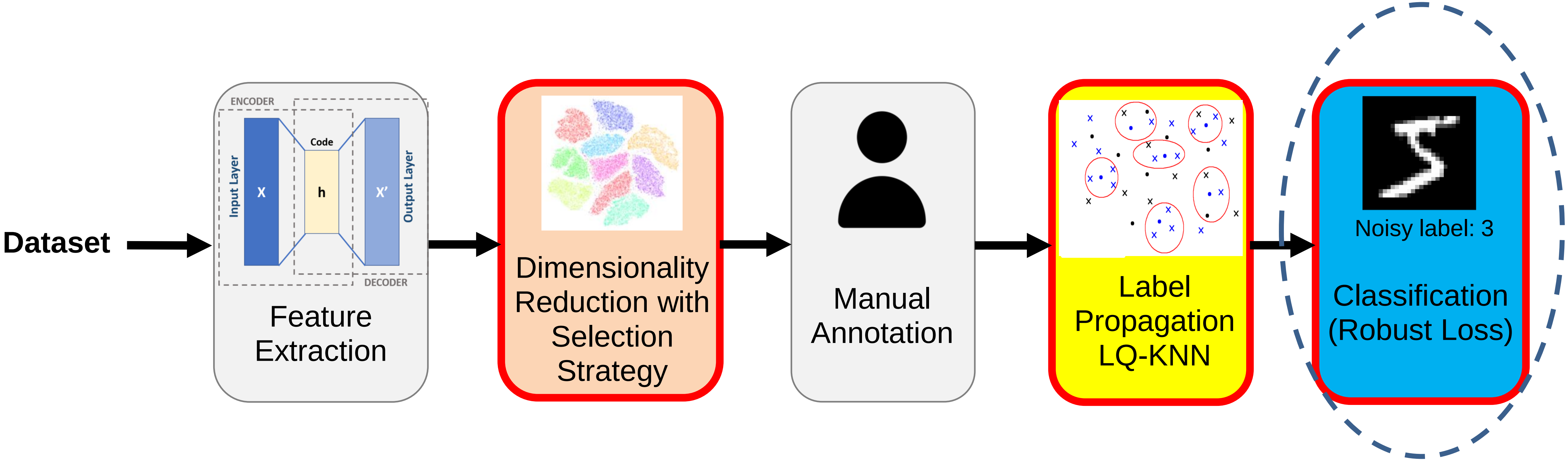
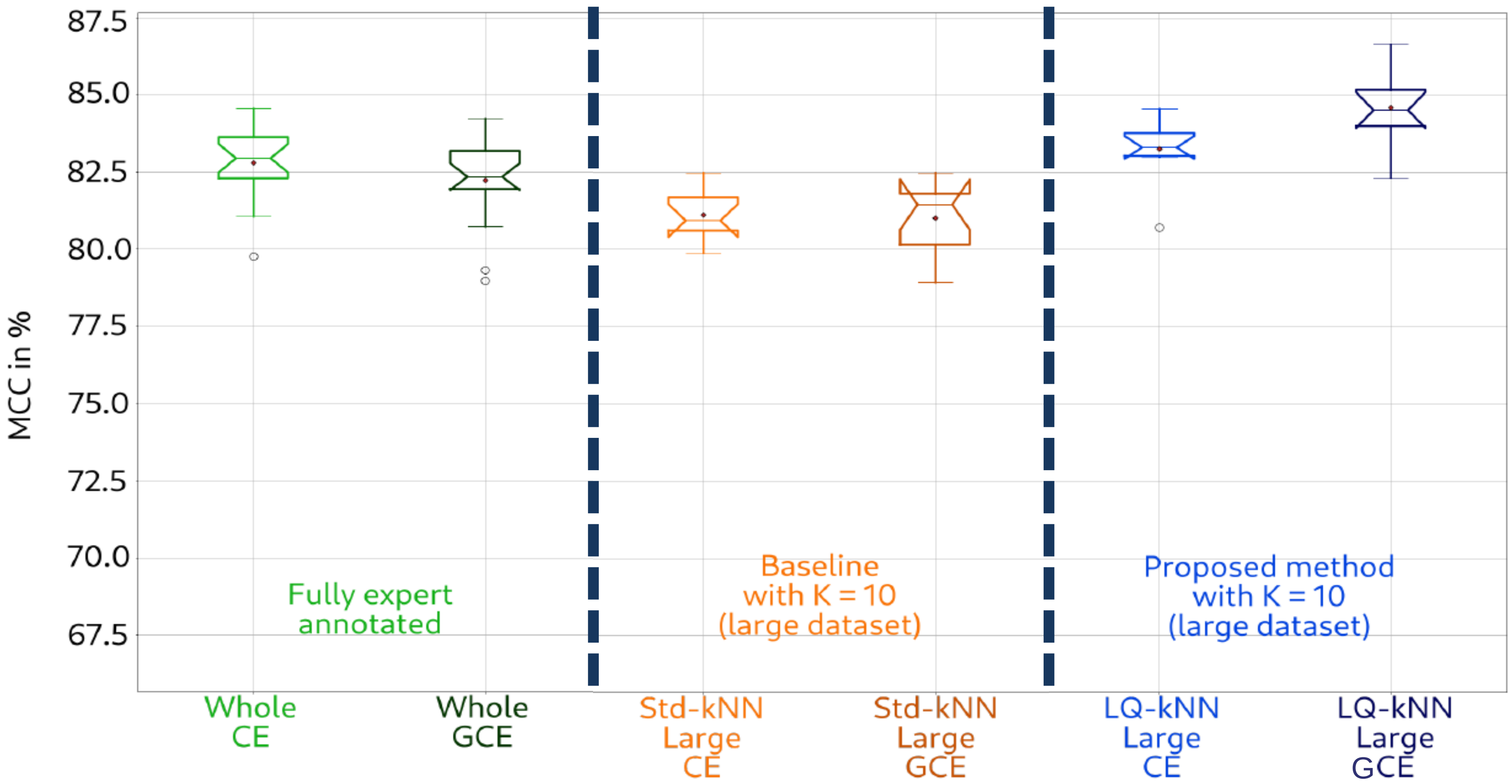


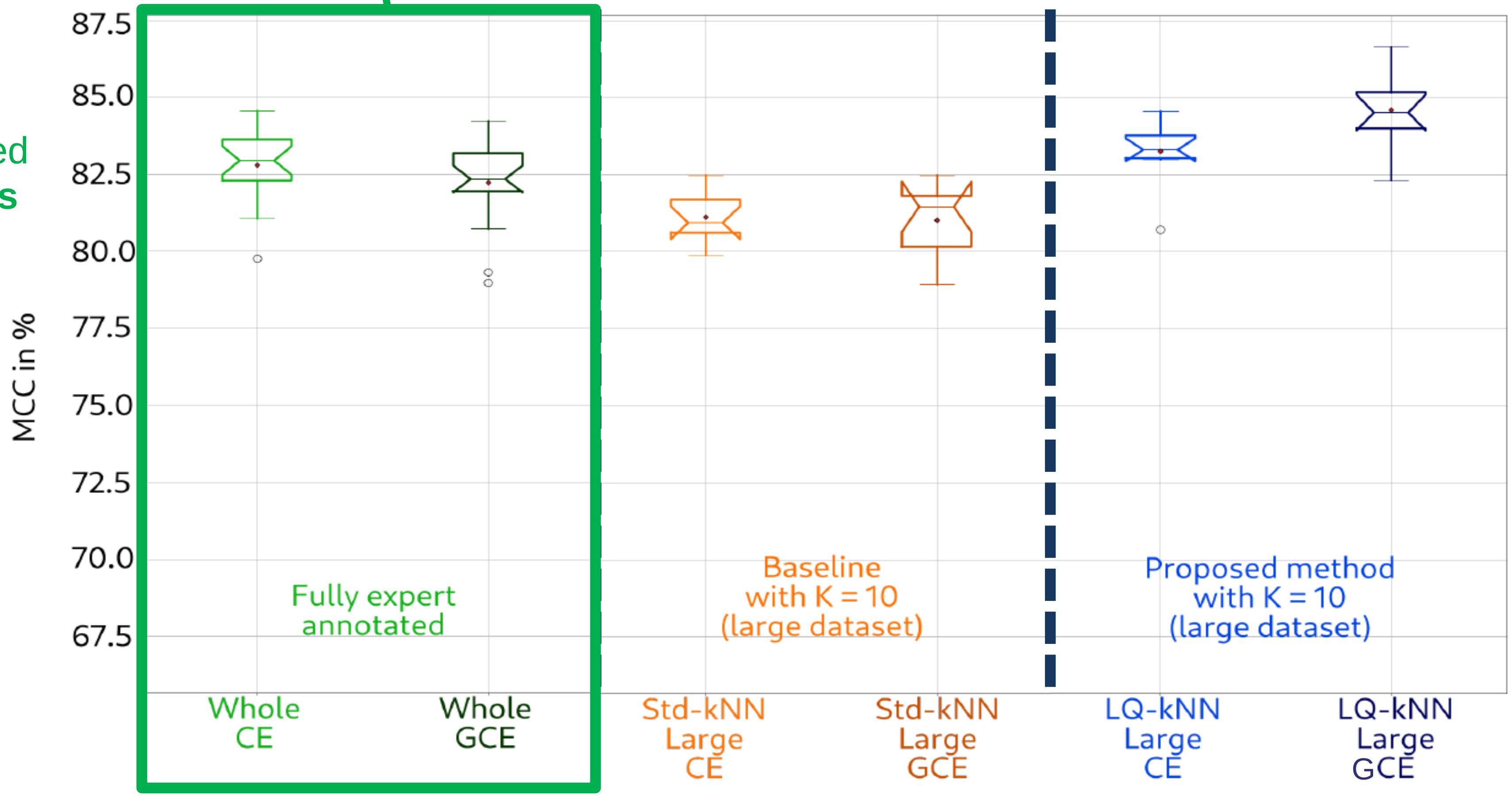
FIGURE - Semi-Automatic Data Annotation Method

Contribution 1.c: Classification with **robust loss** functions on a **2D CNN** model to **compensate** the **noisy-labels**.



Contribution 1.c: Classification with **robust loss** functions on a **2D CNN** model to **compensate** the **noisy-labels**.

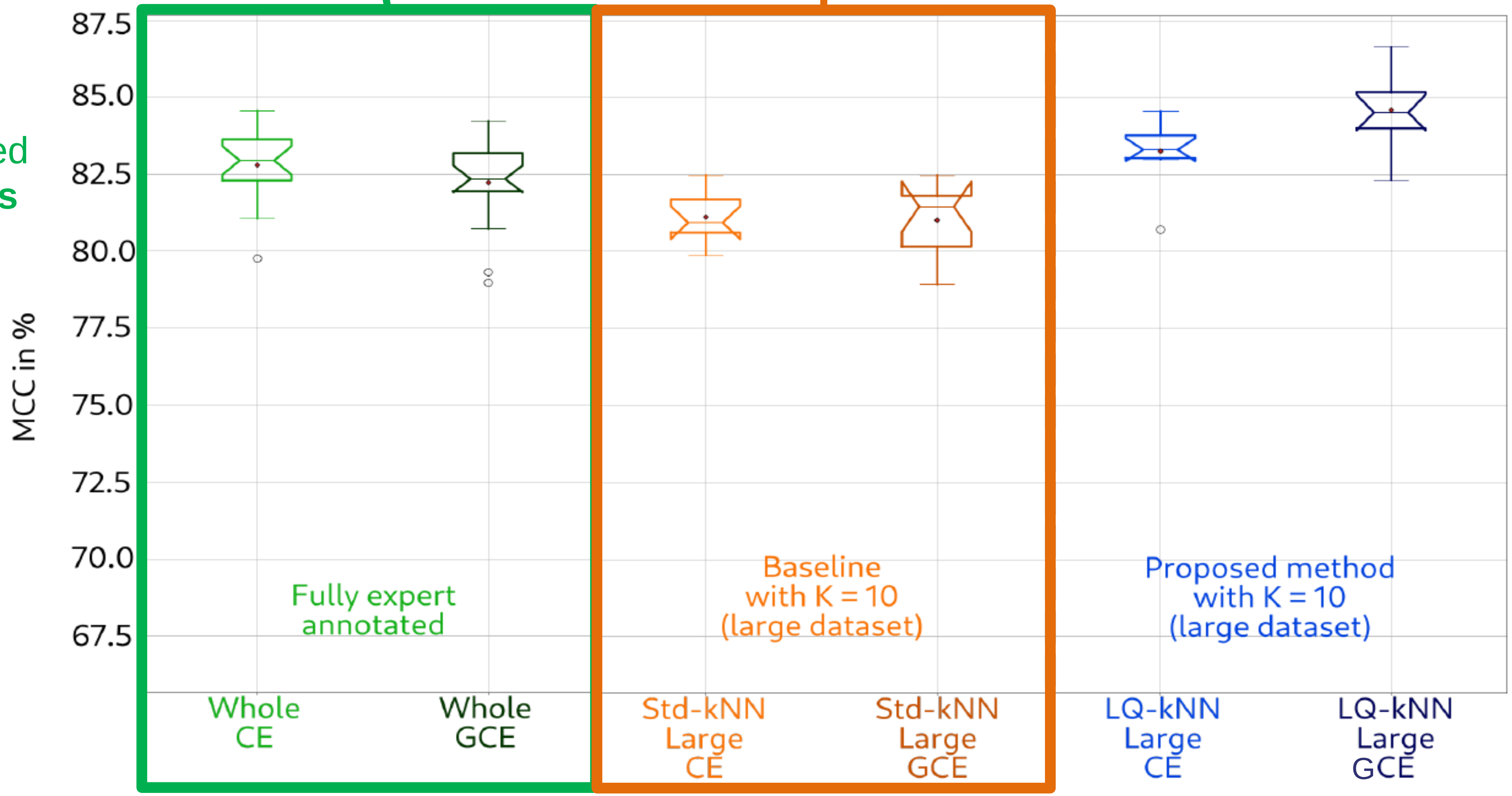
Fully **manually labeled** HITS dataset composed of **1 545 samples**



Contribution 1.c: Classification with **robust loss** functions on a **2D CNN** model to **compensate** the **noisy-labels**.

Dataset composed of **13 653 labeled samples**: **1 545 manually** labeled and **12 108** labeled **with Std-KNN**

Fully **manually labeled** HITS dataset composed of **1 545 samples**

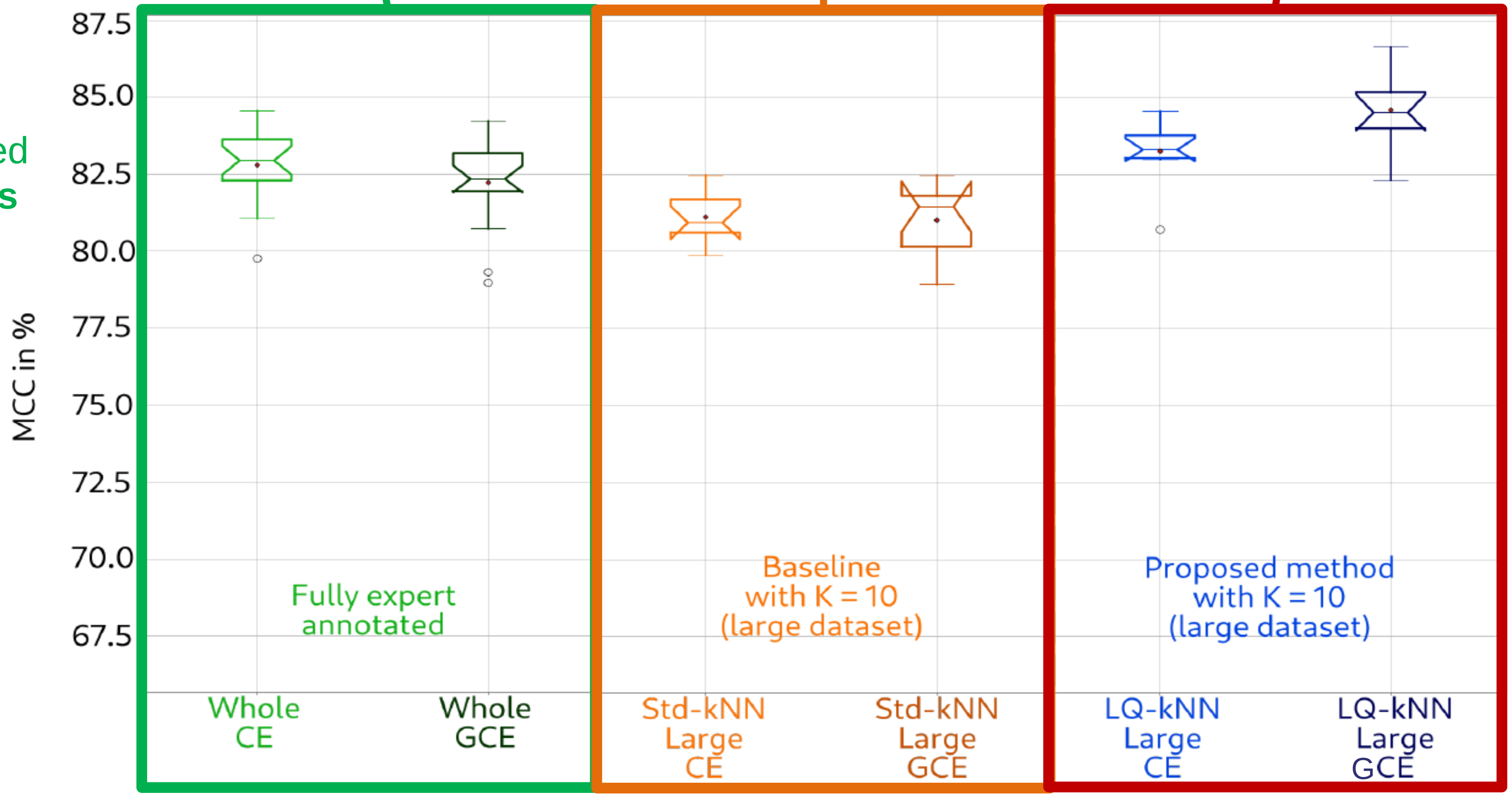


Contribution 1.c: Classification with **robust loss** functions on a **2D CNN** model to **compensate** the **noisy-labels**.

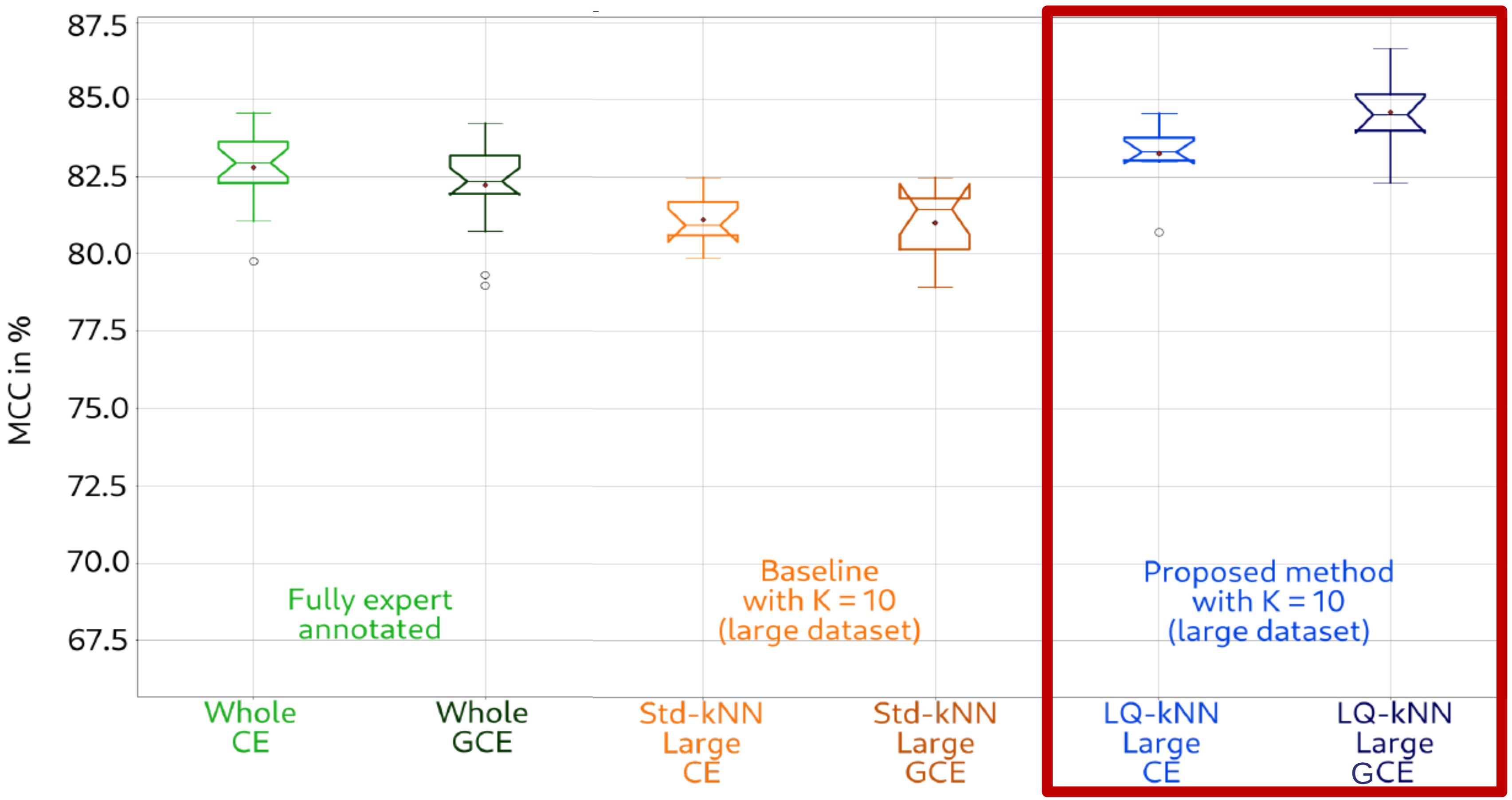
Dataset composed of **13 653 labeled samples**: **1 545 manually** labeled and **12 108** labeled **with Std-KNN**

Fully **manually labeled** HITS dataset composed of **1 545 samples**

Dataset composed of **14 970 labeled samples**: **1 545 manually** labeled and **13 425** labeled **with our LQ-KNN**



Contribution 1.c: Classification using robust loss functions to compensate the noise in the labels.



Improvement of 1.78 % with respect to original dataset

Intermediate conclusion

- **Proposed method** outperforms:
  - Baseline (*Std-kNN*).
  - OPF-Semi.

  ==> **State-of-the-art performances**.

- Proposed method allows to **control** the **annotation error**.

- Optimal projection **selection strategy**:

  ==> **Improves** the **automatic annotation** process.

- **Classification**:
  - Performances **improved** thanks to semi-automatic data annotation.
  - **Robust loss** functions **compensate** label-**noise**.

  ==> **Up to 6 %** accuracy improvement.

Objectives and Contributions

Dataset creation and annotation

- Semi-supervised data annotation*
- Soft labelling (annotation)*

Multiple representations

- Different models with different inputs**
- Multi-feature models

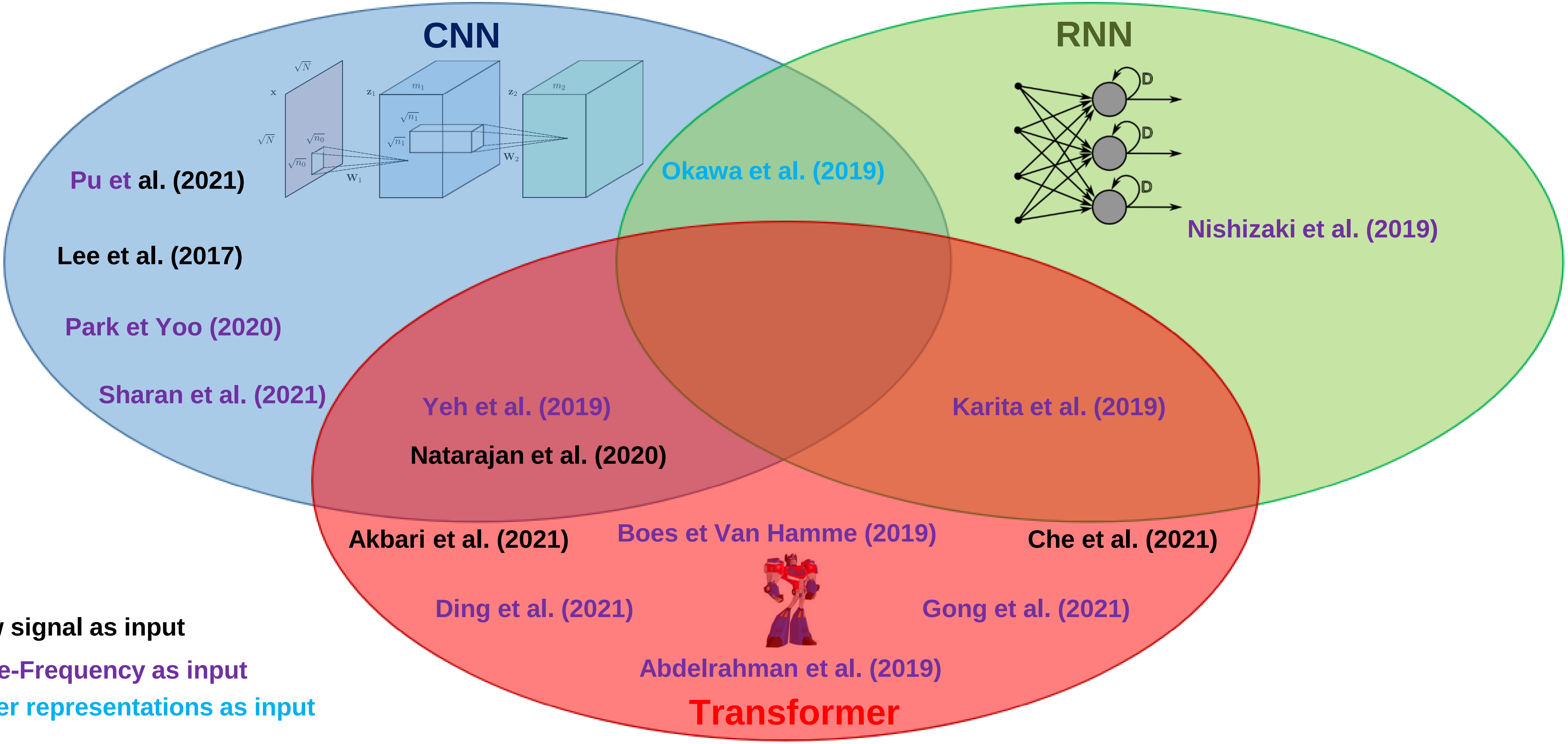
Resource hungry models

- Lite models
- Model compression
- (Soft labelling training)

* Vindas et al. (IUS 2021), Vindas et al. (MEDIA 2022), Vindas et al. (IUS 2023)
** Vindas et al. (MLHC 2022), Vindas et al. (IABM 2023), Vindas et al. (EUSIPCO 2023), and Vindas et al. (Pattern Recognition 2023)

Outline

State-of-the-art deep learning signal classification

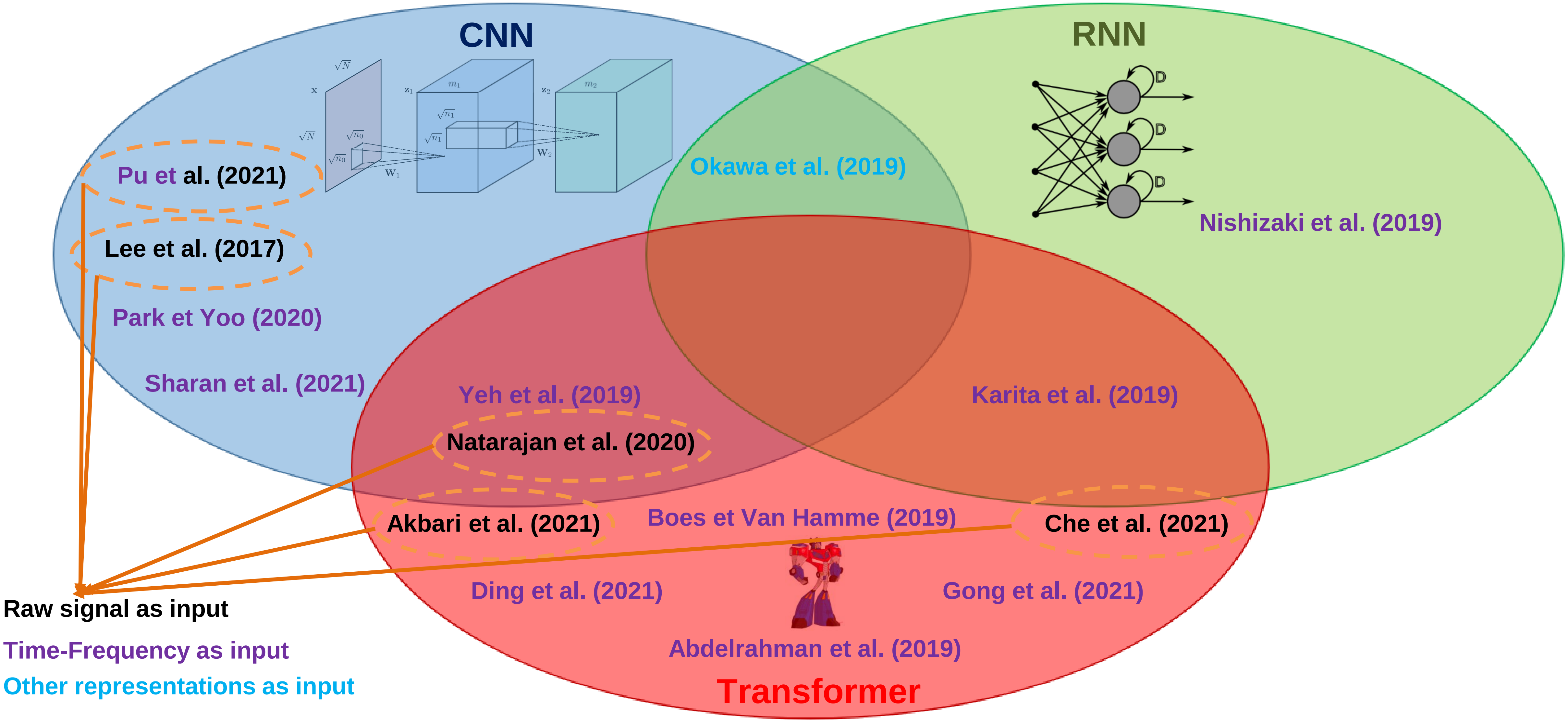


Raw signal as input

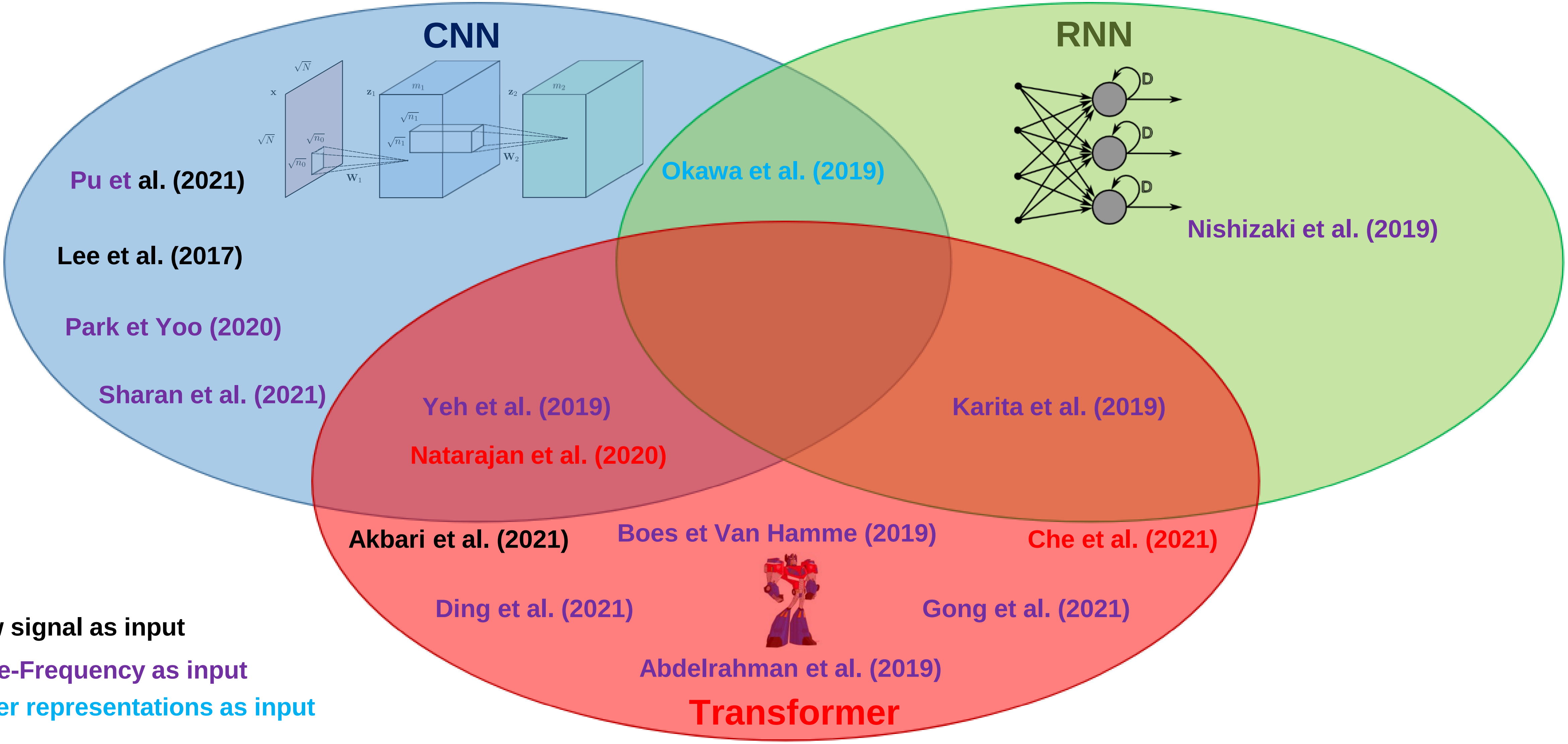
Time-Frequency as input

Other representations as input

State-of-the-art deep learning signal classification



State-of-the-art deep learning signal classification

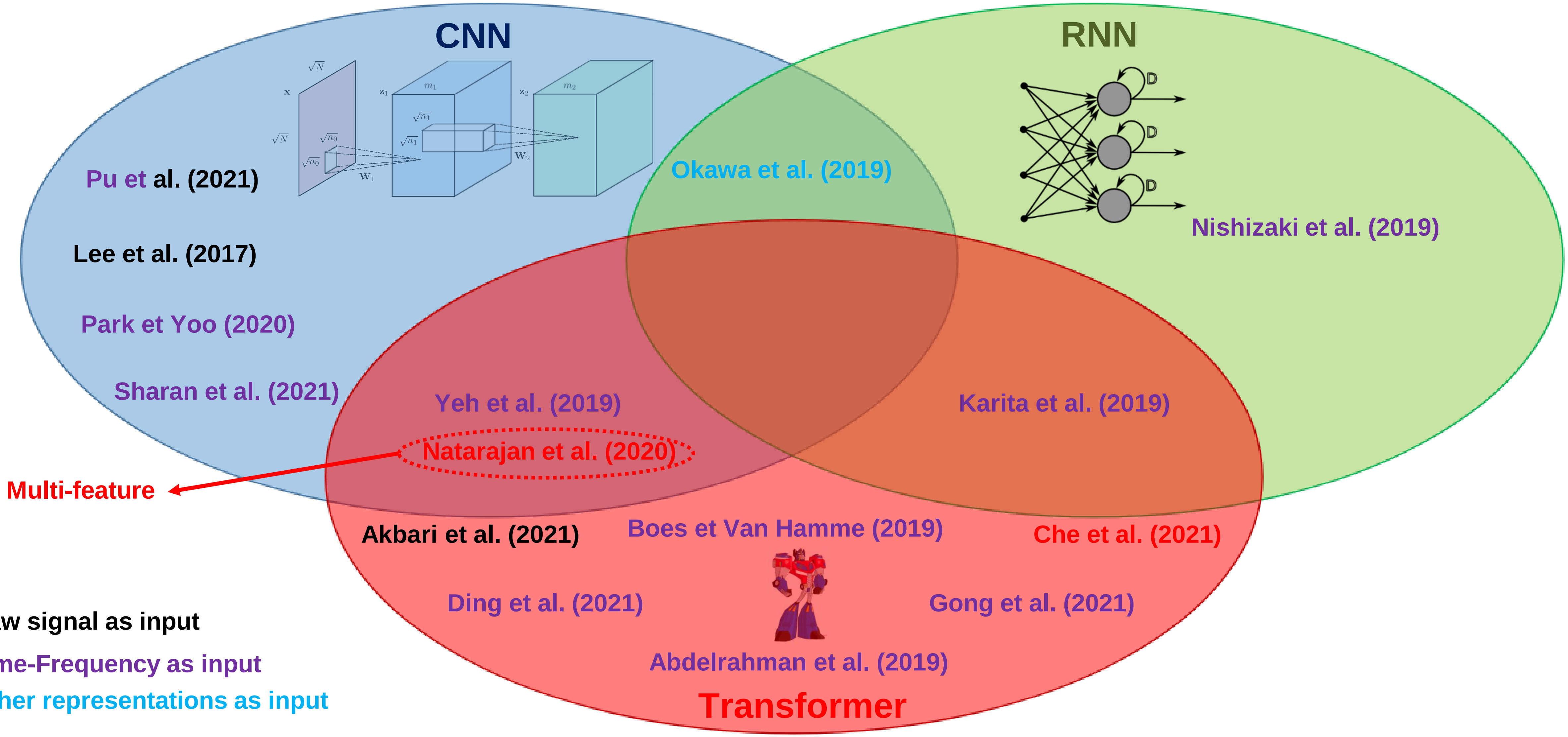


Raw signal as input

Time-Frequency as input

Other representations as input

State-of-the-art deep learning signal classification

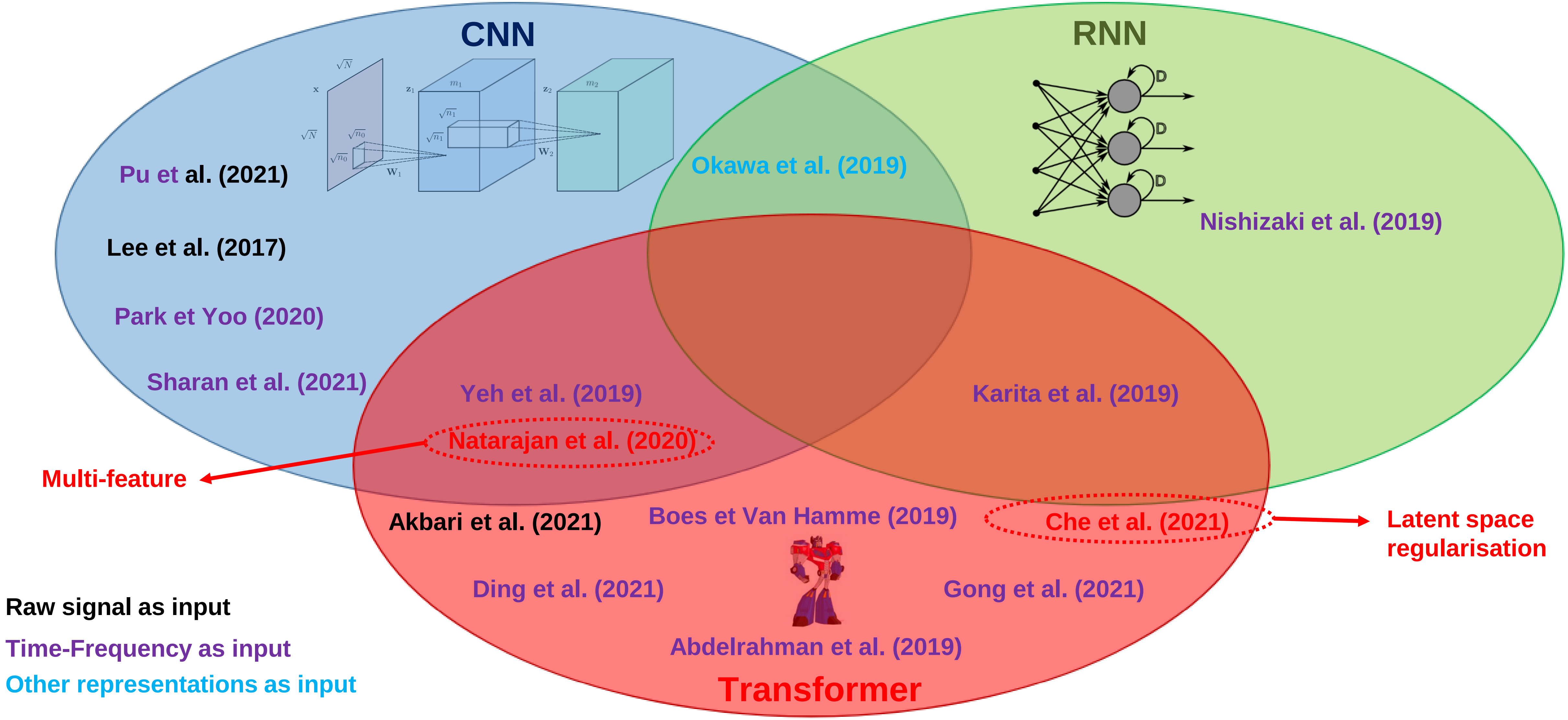


Raw signal as input

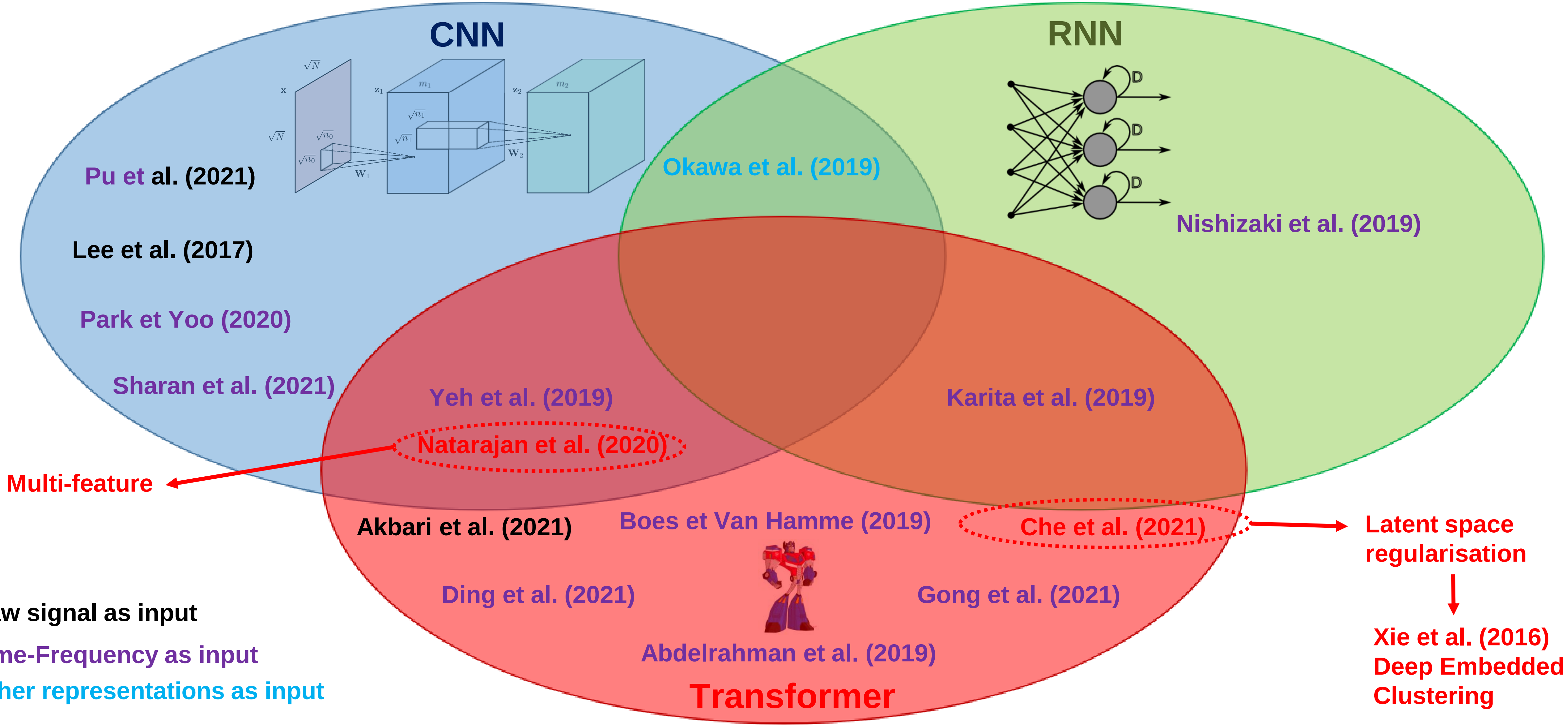
Time-Frequency as input

Other representations as input

State-of-the-art deep learning signal classification



State-of-the-art deep learning signal classification



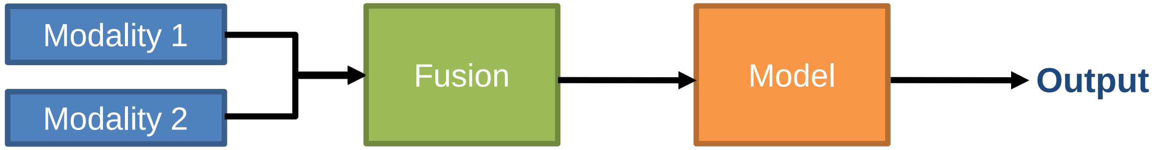
Raw signal as input

Time-Frequency as input

Other representations as input

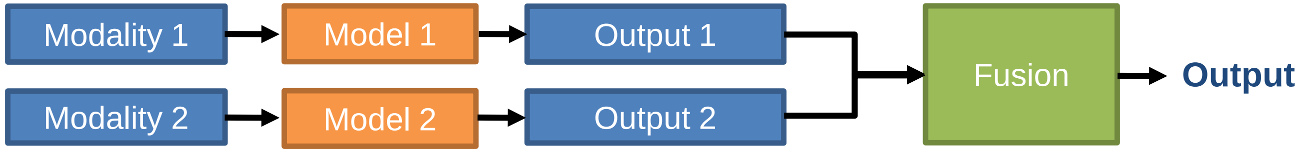
State-of-the-art multi-feature learning

Early fusion



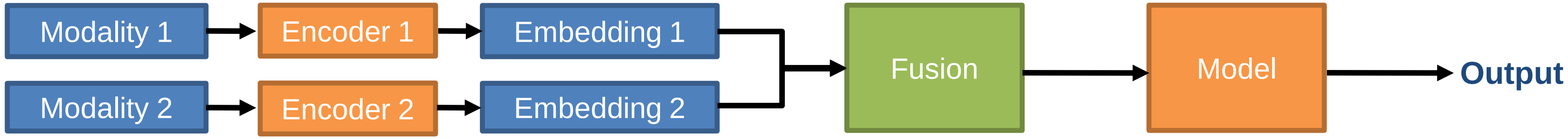
- Zhu et Jiang (2020)
- Ahmad et al. (2021)
- Yao et al. (2021)
- Wang et al. (2016)
- Feng et al. (2020)
- Kim et Lee (2019)

Late fusion



- Chen et al. (2021)
- Abdi et al. (2021)

Intermediate fusion



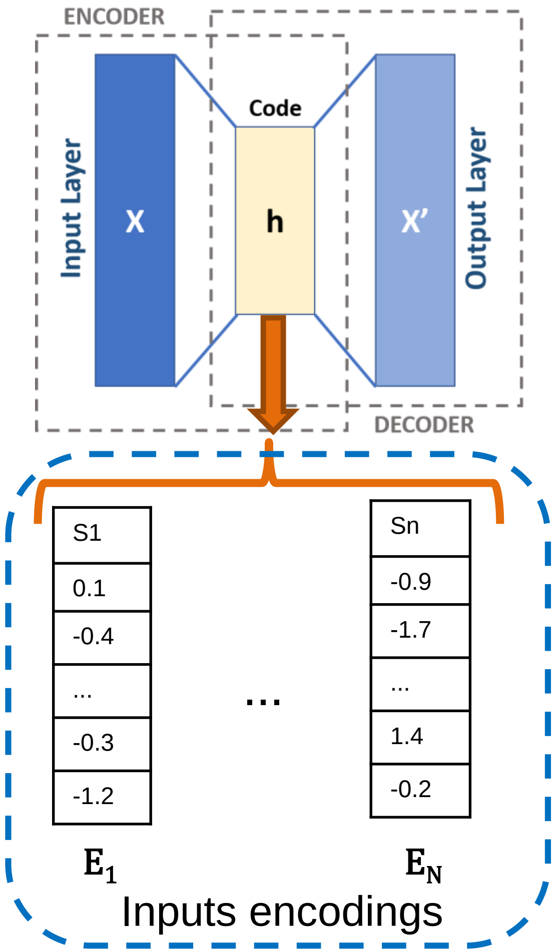
Raw signal as input

Time-Frequency as input

Other representations as input

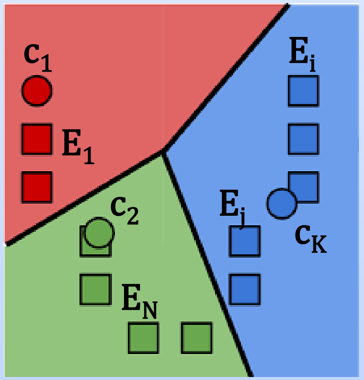
- Mao et al. (2020)
- Tiong et al. (2021)
- Abdi et al. (2021)
- Zhou et al. (2020)
- Zhou et al. (2022)
- Liu (2021)
- Jin et al. (2020)

Deep embedded clustering



Clustering

Initialization



K-means

Soft assignments of E_i to C_j

$$q_{ij} = \frac{\sum_{p=1}^{K}\left(1+\frac{||E_i - \mathbf{c}_p||^2}{\alpha}\right)^{\frac{\alpha+1}{2}}}{\left(1+\frac{||E_i - \mathbf{c}_j||^2}{\alpha}\right)^{\frac{\alpha+1}{2}}}$$

Clusters soft frequencies

$$f_j = \sum_{p=1}^{K} q_{pj}$$

Target distribution

$$p_{ij} = \frac{\frac{q_{ij}^2}{f_j}}{\sum_{p=1}^{K}\frac{q_{ip}^2}{f_p}}$$

Properties
- Cluster purity.
- Focus on high confidence samples.
- Normalization of the contribution of each centroid to the final loss.

DEC loss function

$$\mathcal{L}_{DEC} = KL(P||Q)$$

Figure – Deep embedded clustering for unsupervised learning (**Xie et al., 2016**)

Outline

Claims of contribution 2

a. Novel **hybrid CNN-transformer** models, **exploiting** the **complementarity** between the **temporal** and **spectral characteristics** of a medical signal.

b. **Guided** and **regularized intermediate fusion** approach, improving generalization while handling **imbalanced** datasets and **label-noise**.

c. **Late-fusion** mechanisms, based on **learnable** and **interpretable attention weights**.

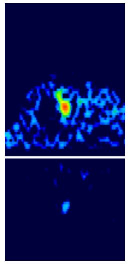
Proposed approach

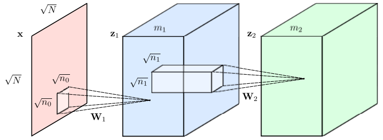
Objectives:

- Improve the classification of TCD signals.
- Exploit the complementarity of different representations.

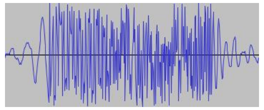
Models:

- 2D CNN model for TFRs.

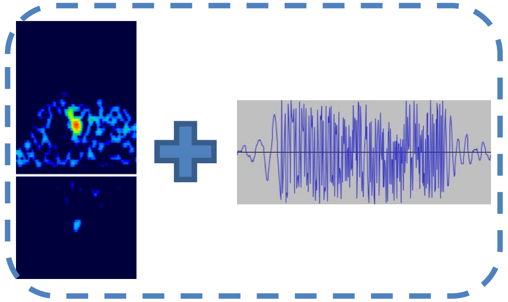


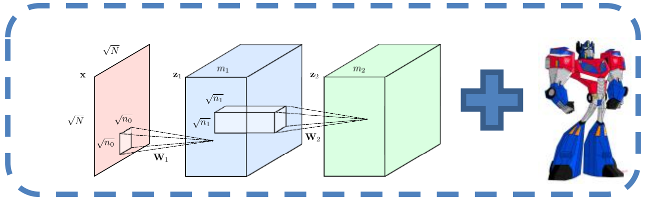


- 1D CNN-Transformer for raw signals.



- **Hybrid models for both representations.**





Single feature TFR 2D CNN

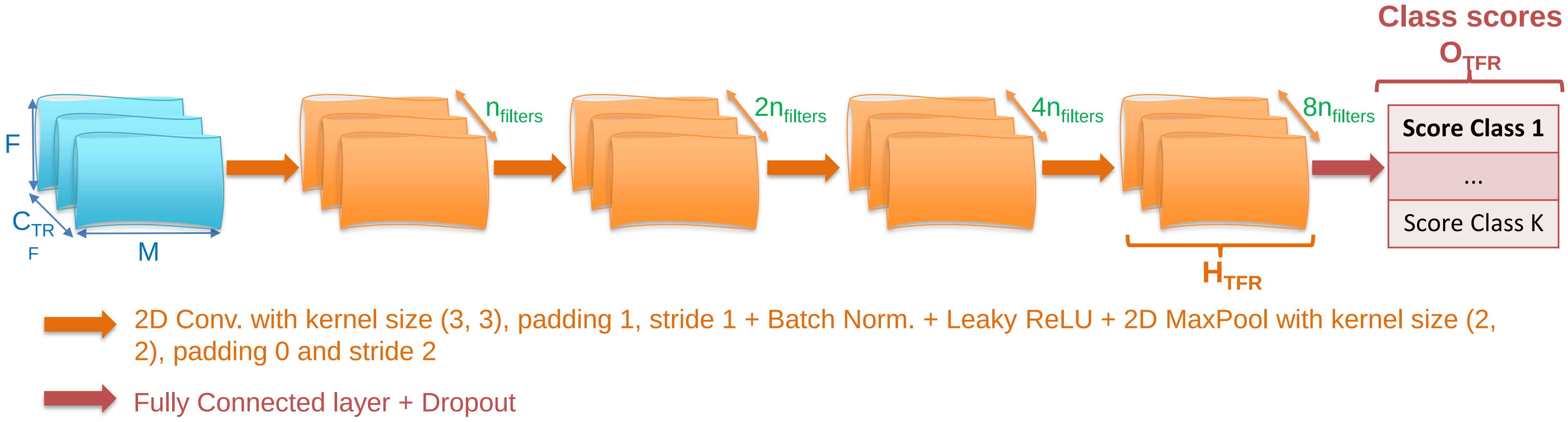


Figure - Proposed 2D CNN

Single feature raw signal 1D CNN-transformer

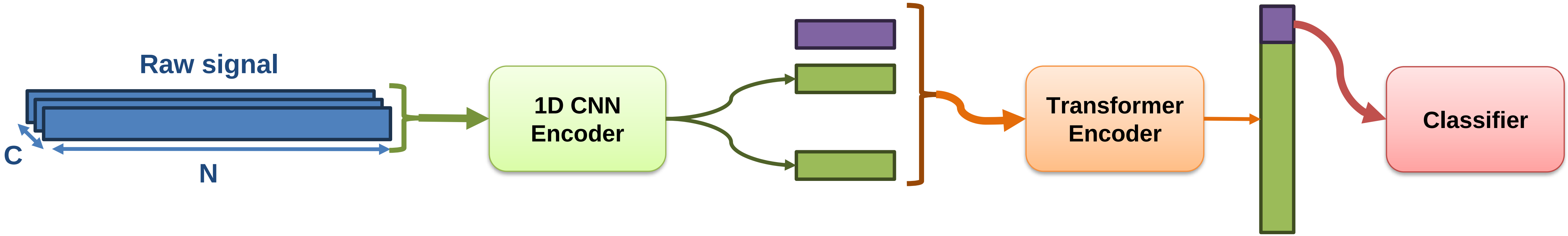


Figure - Proposed 1D CNN Transformer architecture (inspired from Natarajan et al. 2020).

Single feature raw signal 1D CNN-transformer

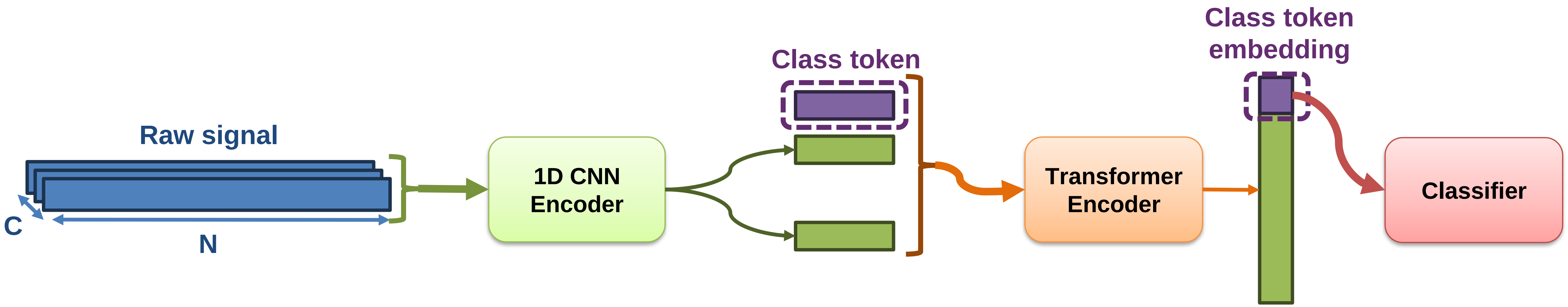


Figure - Proposed 1D CNN Transformer architecture (inspired from Natarajan et al. 2020).

Guided and regularized intermediate fusion

Figure - Proposed **intermediate fusion** hybrid CNN Transformer model.

Guided and regularized intermediate fusion

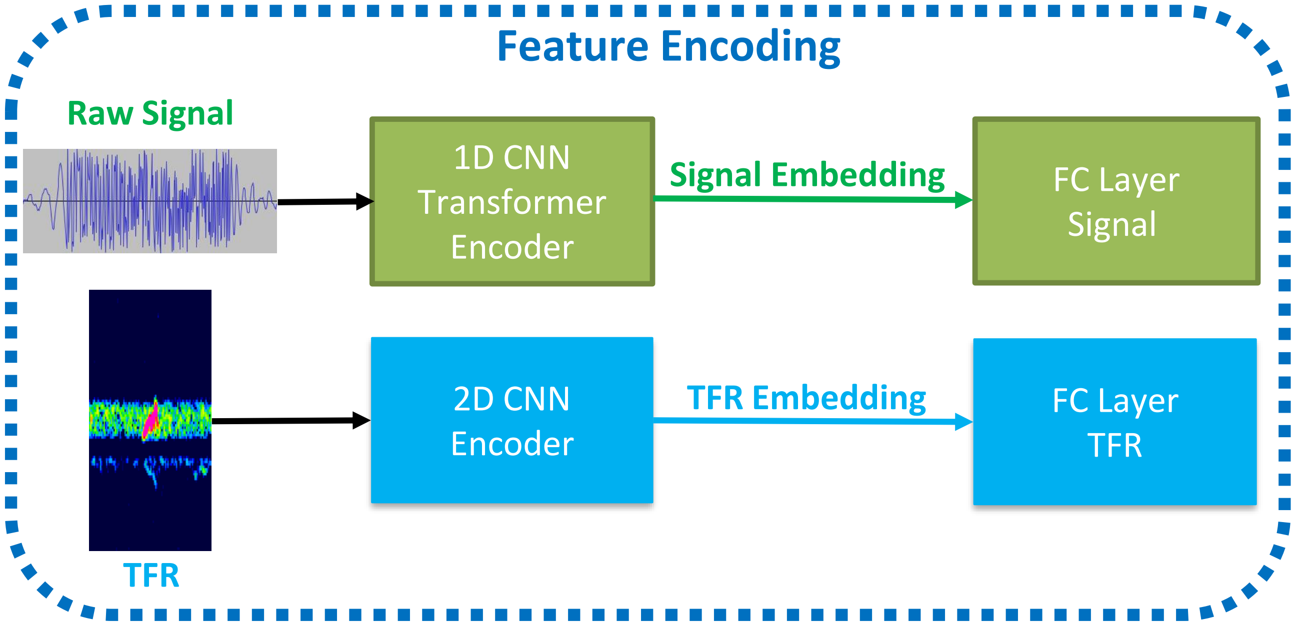


Figure - Proposed **intermediate fusion** hybrid CNN Transformer model.

Guided and regularized intermediate fusion

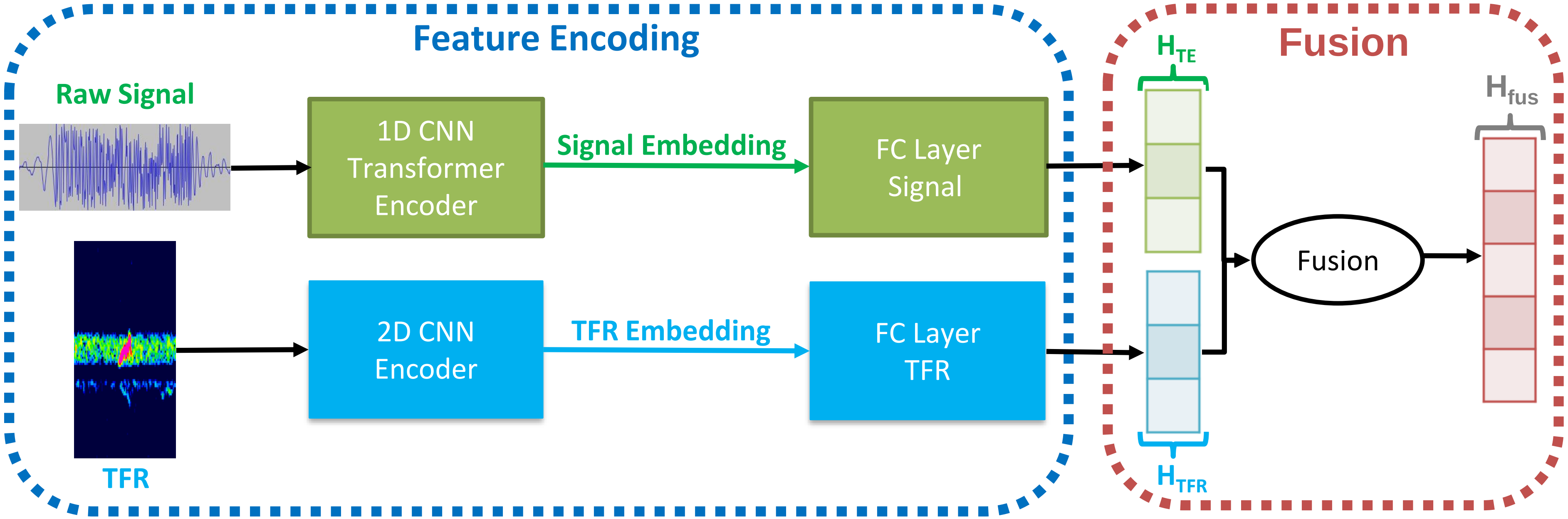


Figure - Proposed **intermediate fusion** hybrid CNN Transformer model.

Guided and regularized intermediate fusion

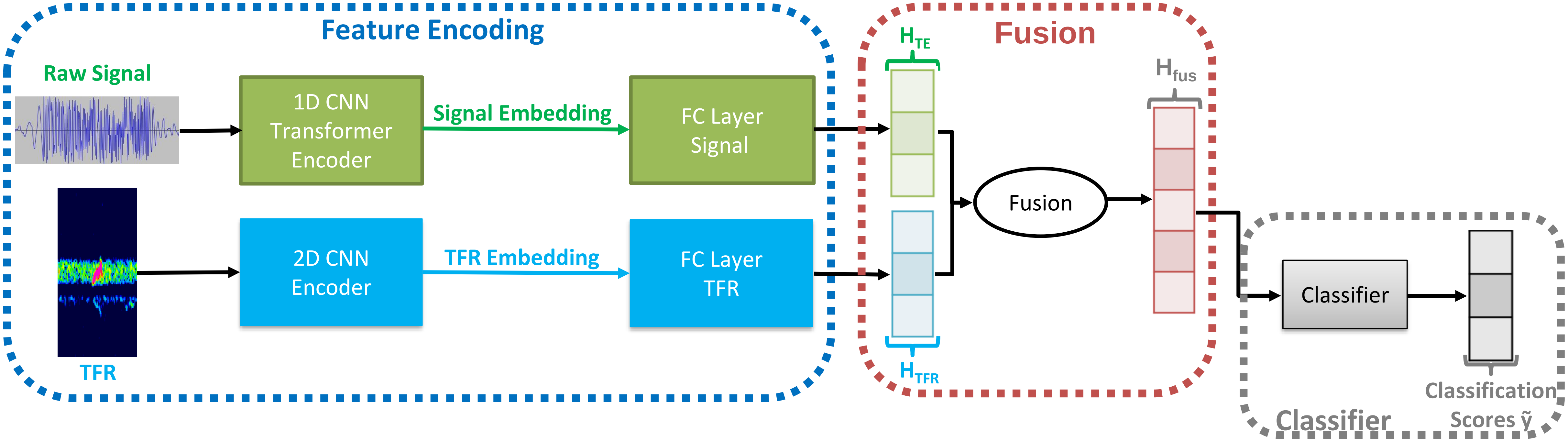


Figure - Proposed **intermediate fusion** hybrid CNN Transformer model.

Guided and regularized intermediate fusion

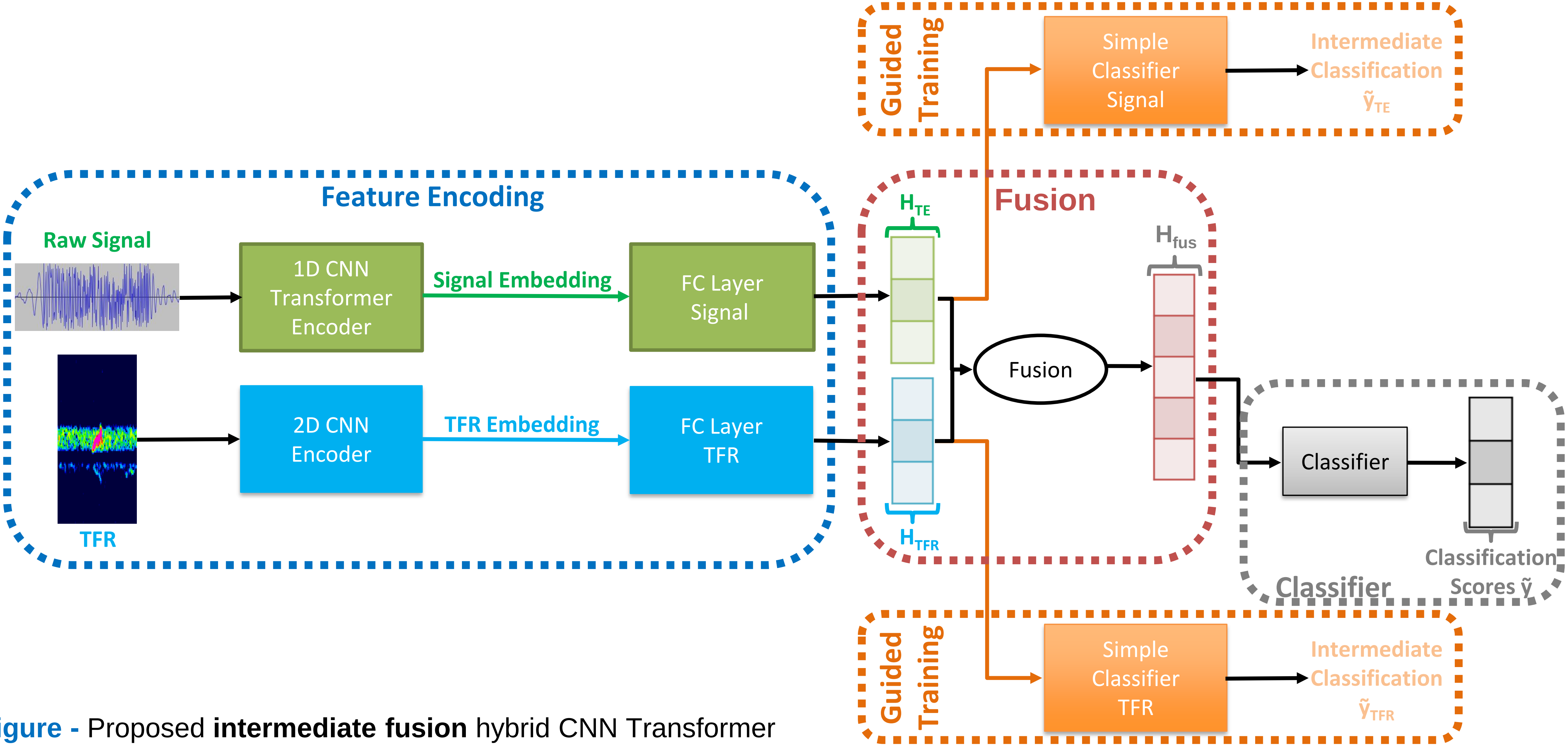


Figure - Proposed **intermediate fusion** hybrid CNN Transformer model.

Guided and regularized intermediate fusion

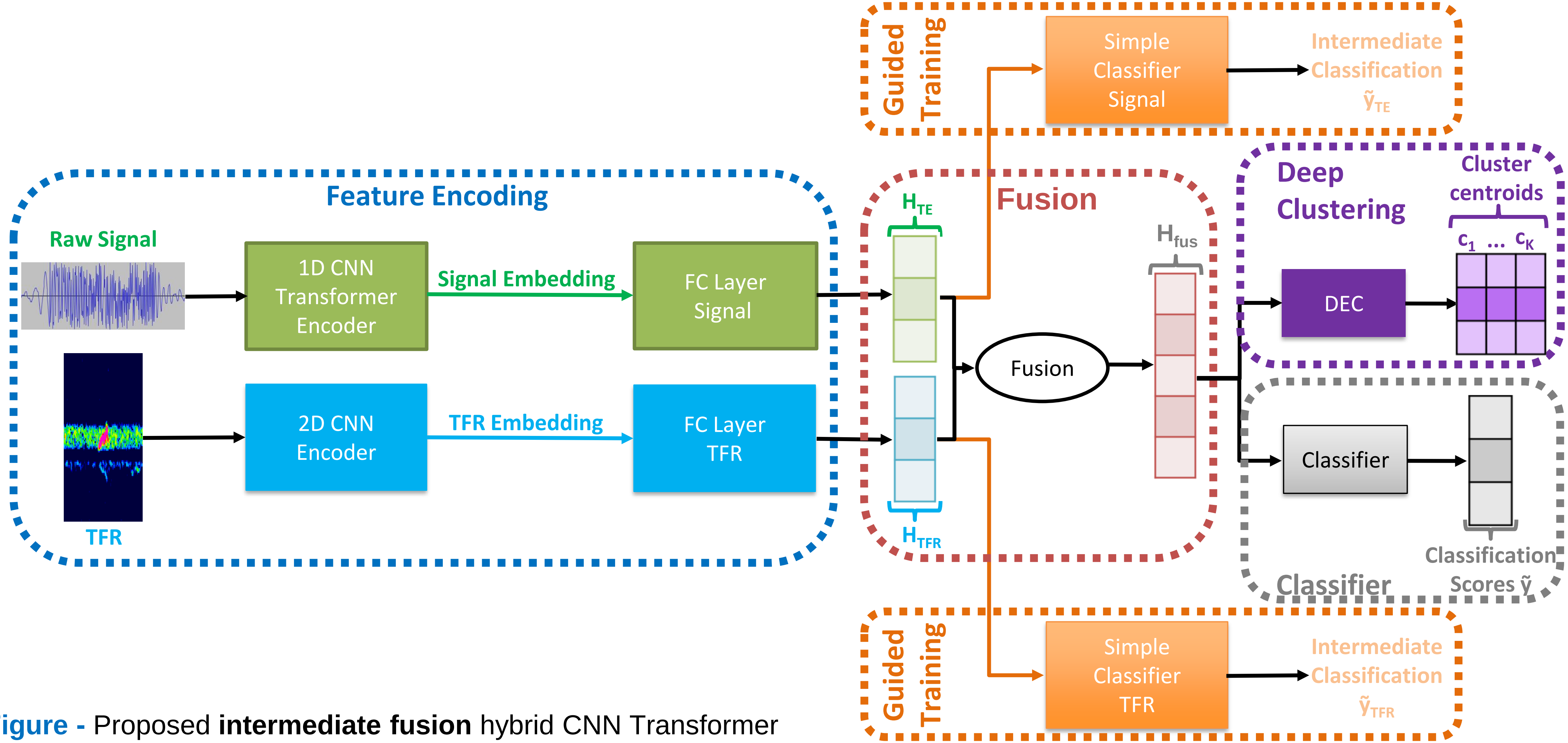


Figure - Proposed **intermediate fusion** hybrid CNN Transformer model.

Intermediate fusion

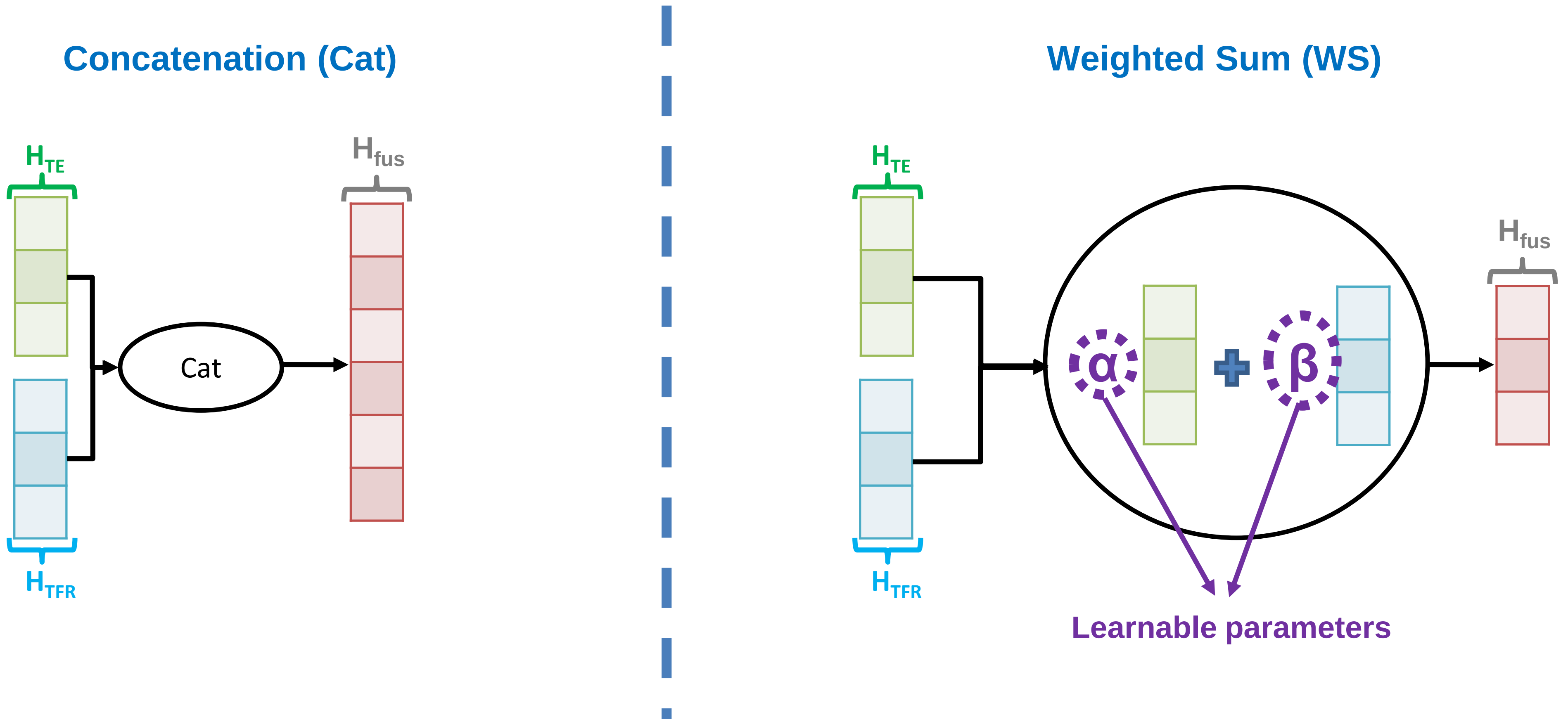


Figure - Proposed intermediate fusion strategies: concatenation and weighted sum

Outline

Experiment: SOTA comparison

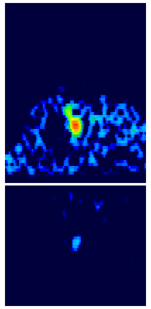
Objective:

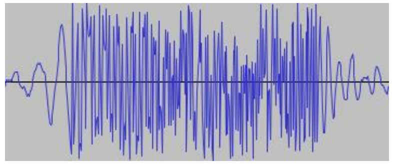
- Highlight the advantage of multi-feature classification.
- Comparison with multi-feature SOTA methods.

Datasets:

HITS:

- TCD Data.
- 1545 samples.
- Three classes.
- Sampling frequency: 4385 Hz.





Metrics:

- Mathews Correlation Coefficient (MCC).

Loss function:

- Cross entropy (CE)

Class	Number of samples
Artifact	403
Gaseous Emboli	569
Solid Emboli	569
Unknown	4

Results

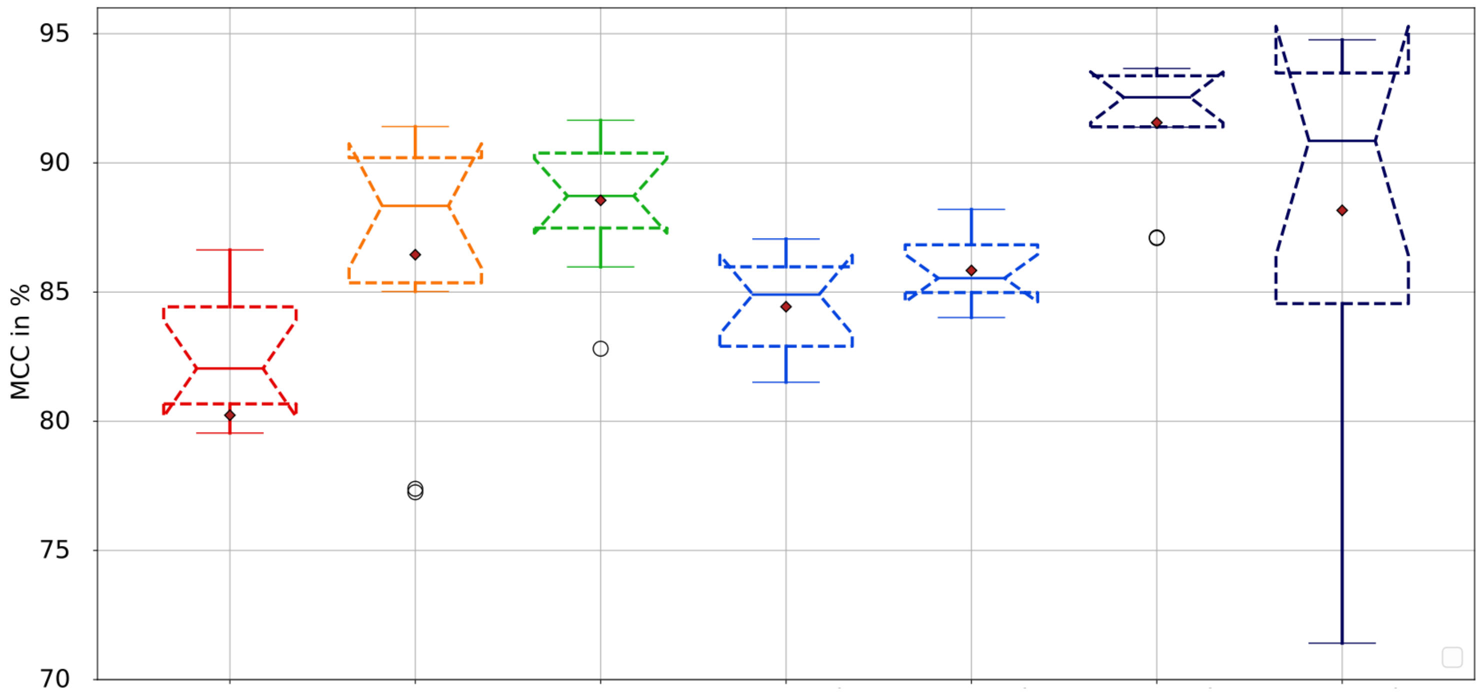
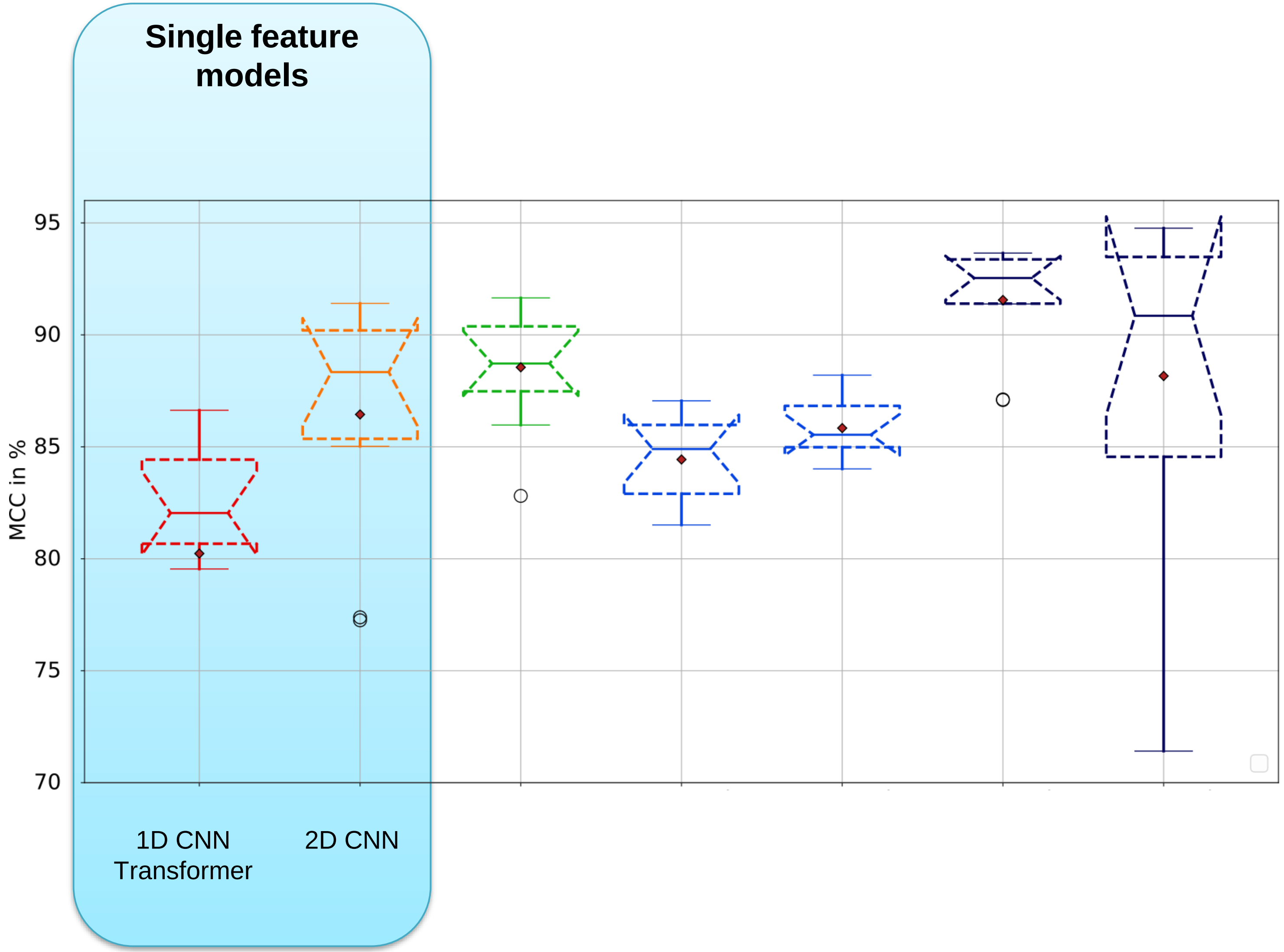


Figure - Comparison of the classification performances of different single and multi-feature models on the HITS dataset

Results



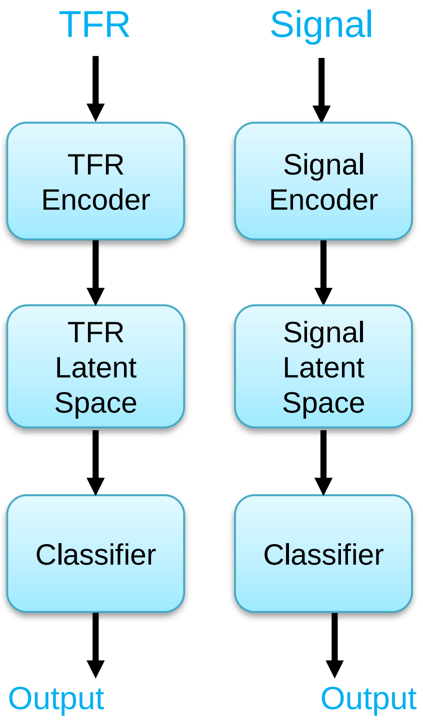


Figure - Comparison of the classification performances of different single and multi-feature models on the HITS dataset

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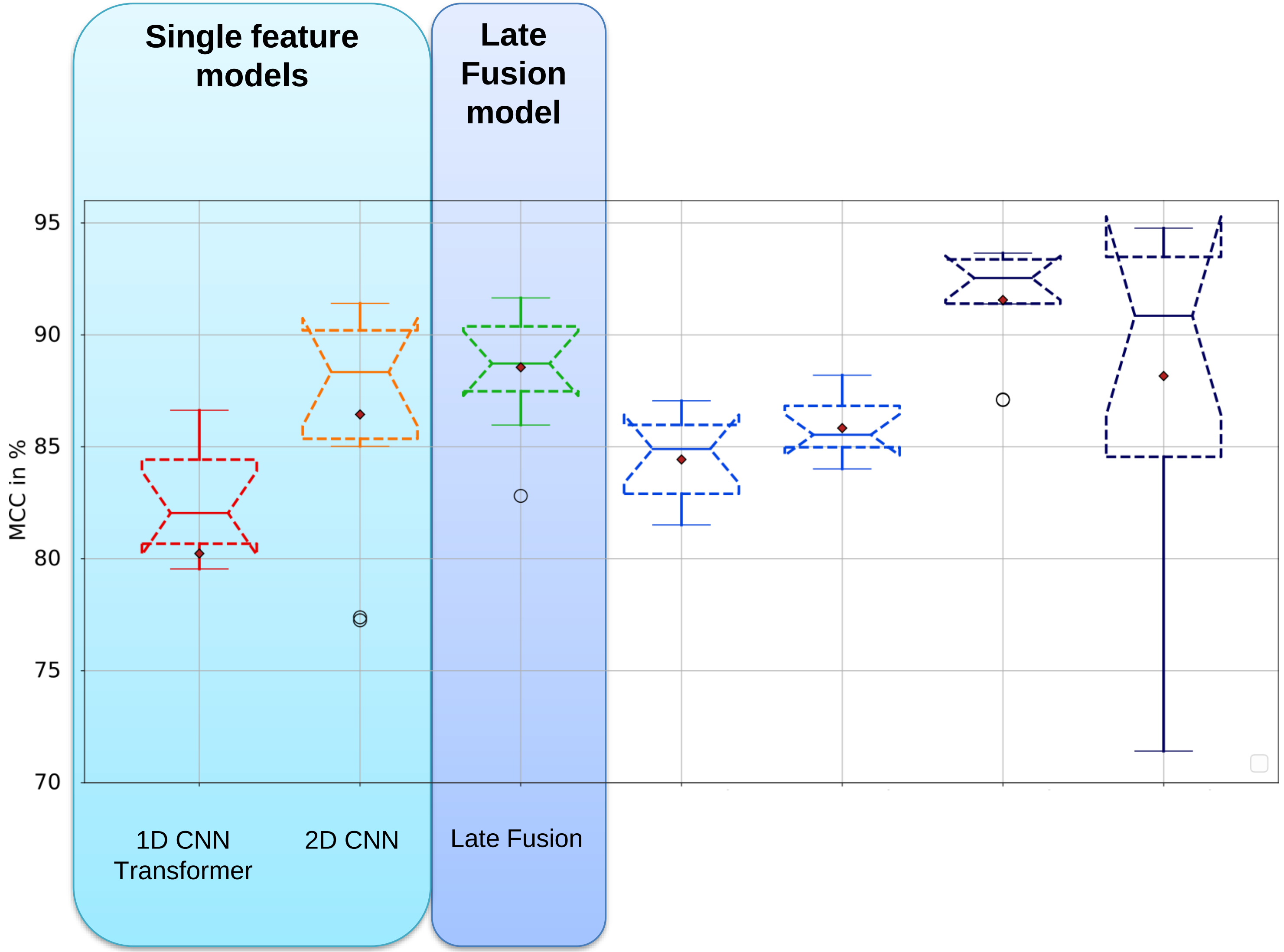

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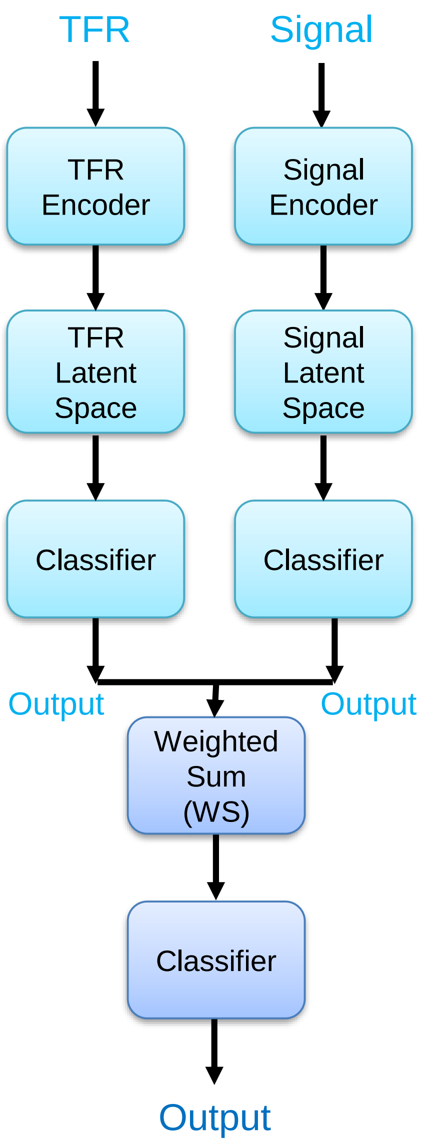


Results

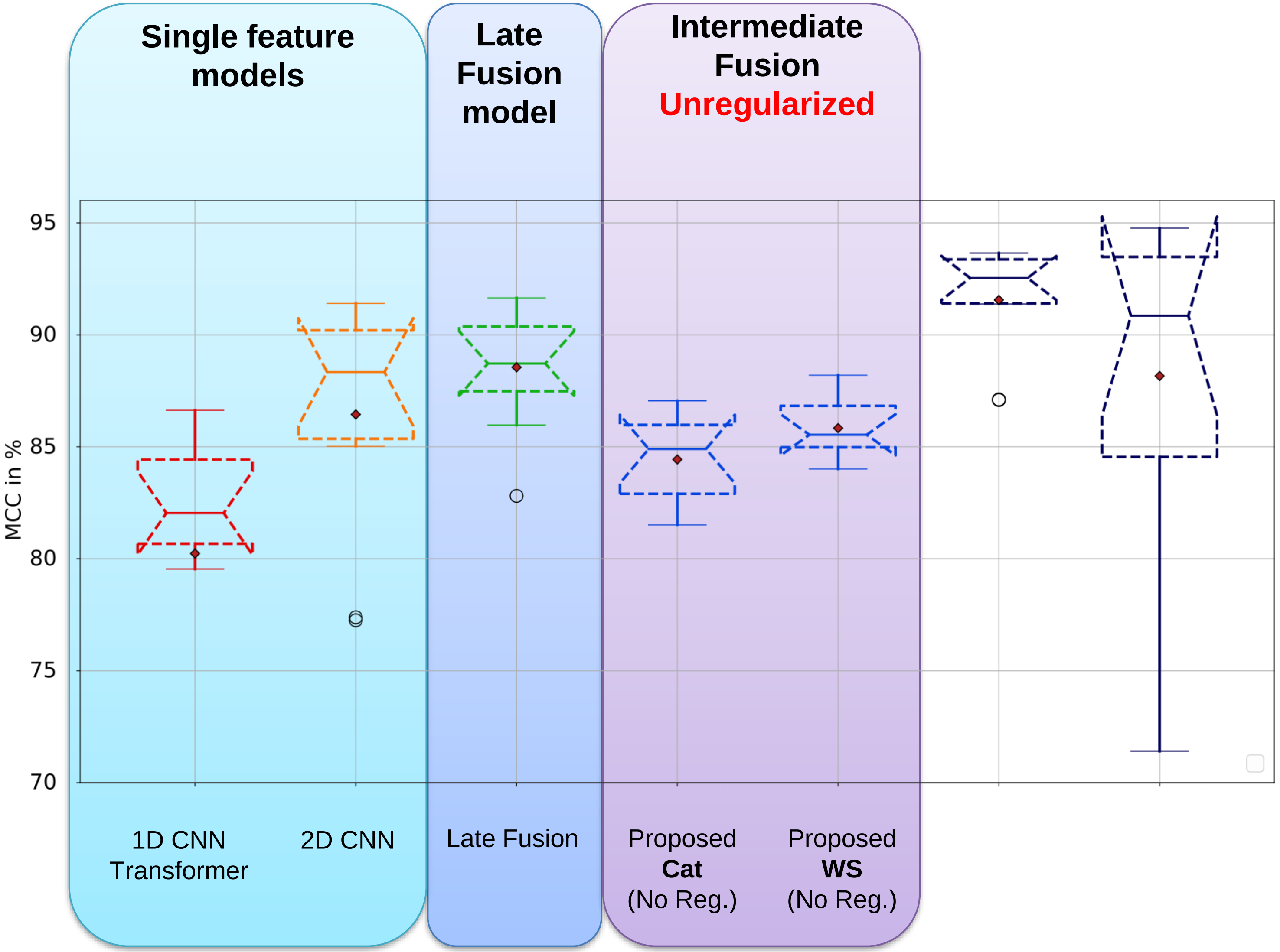
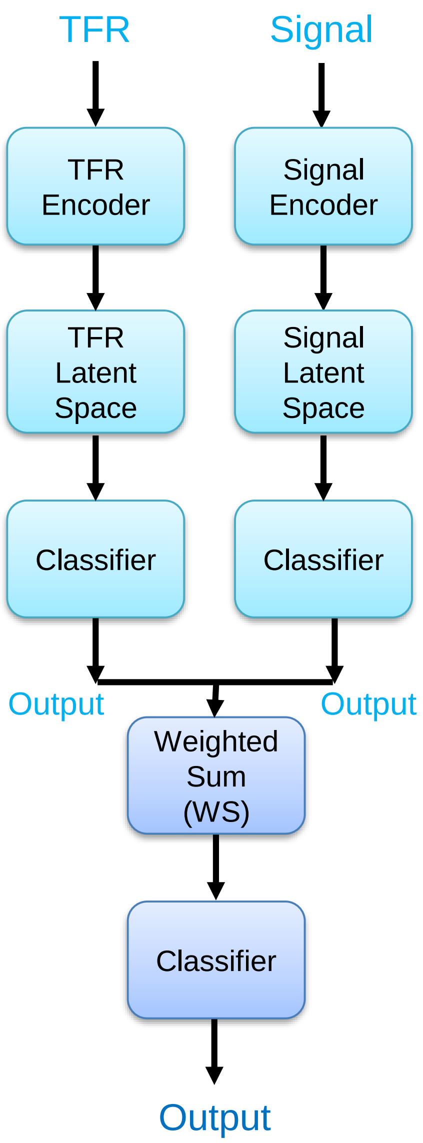
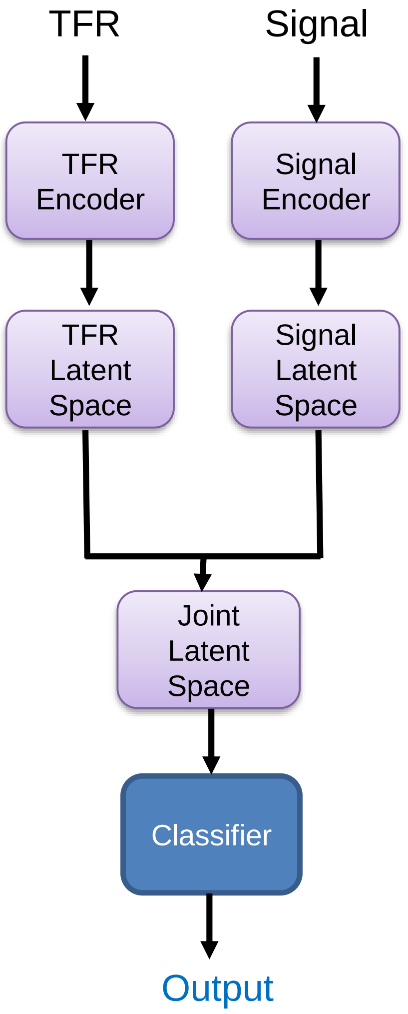
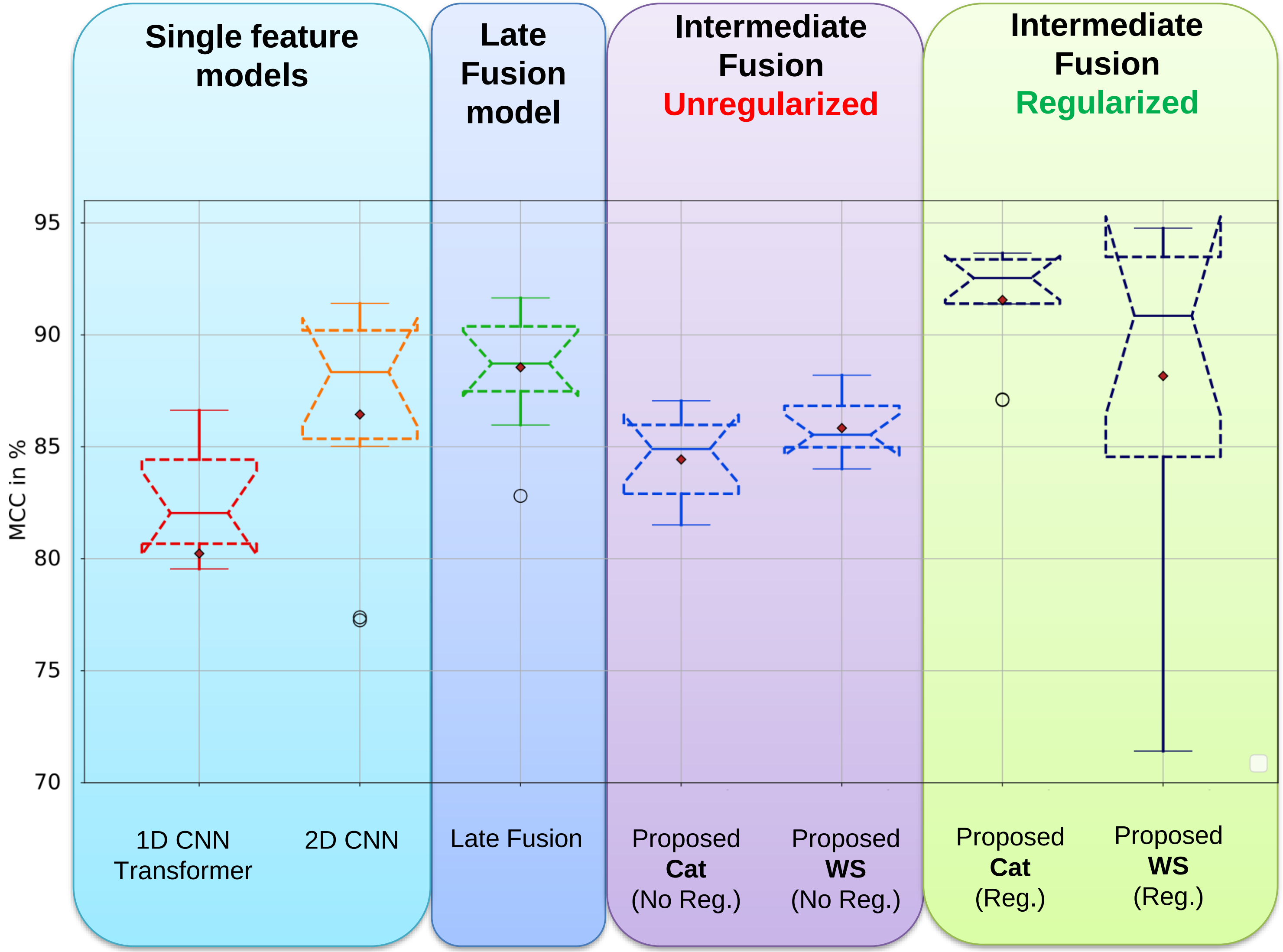


Figure - Comparison of the classification performances of different single and multi-feature models on the HITS dataset





Results



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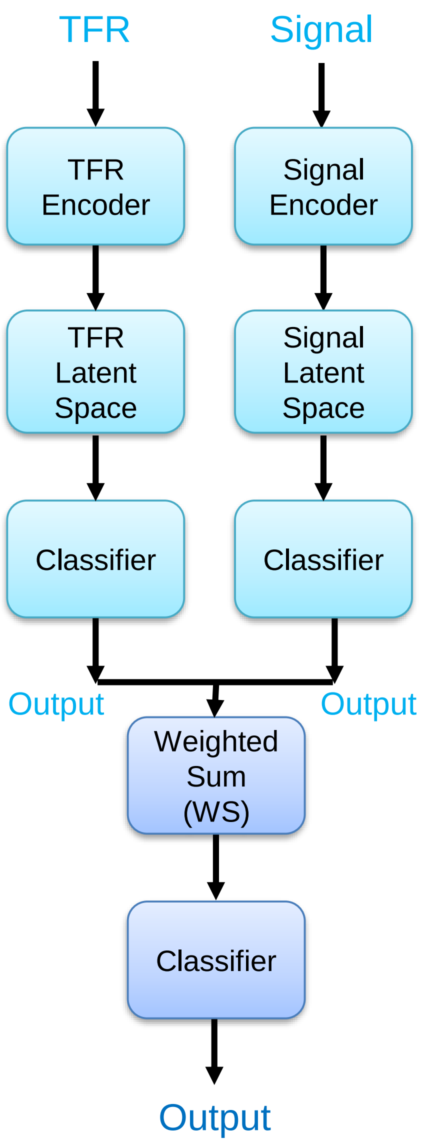
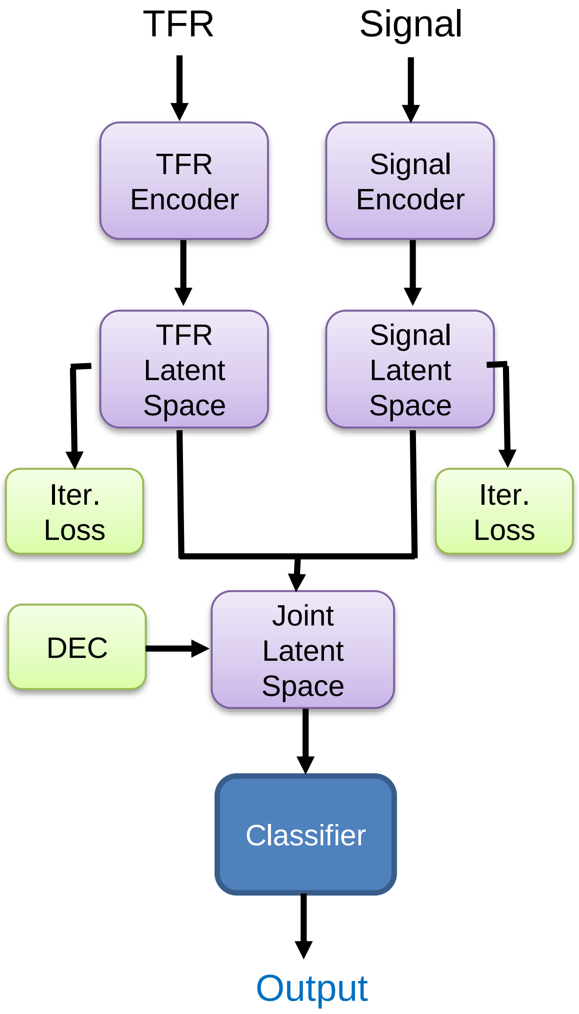




Results

Unregularized

Regularized

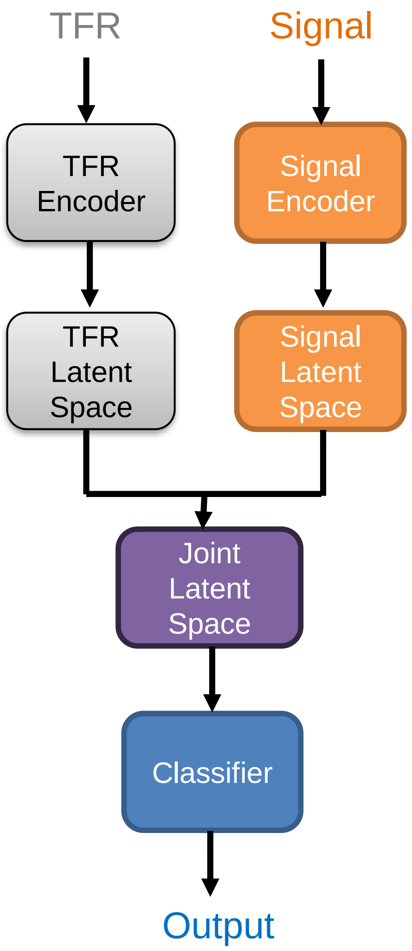
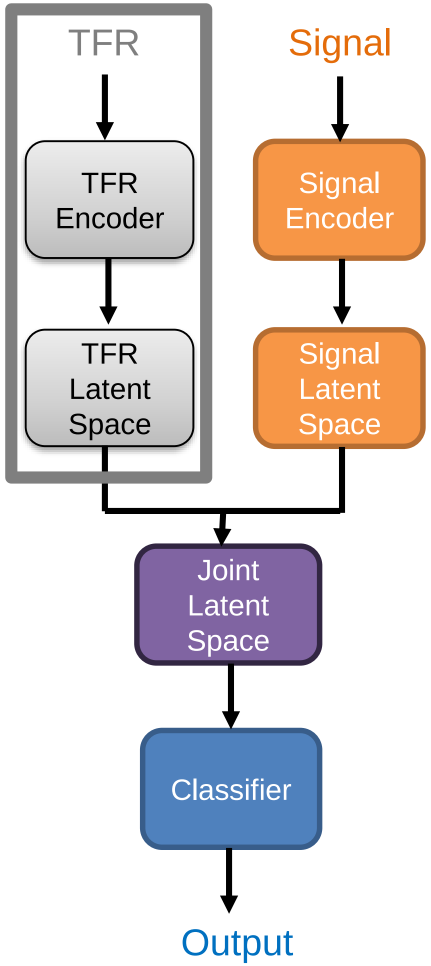


Figure - UMAP projections of the different latent spaces of the multi-feature intermediate fusion classification model on the HITS dataset

Results



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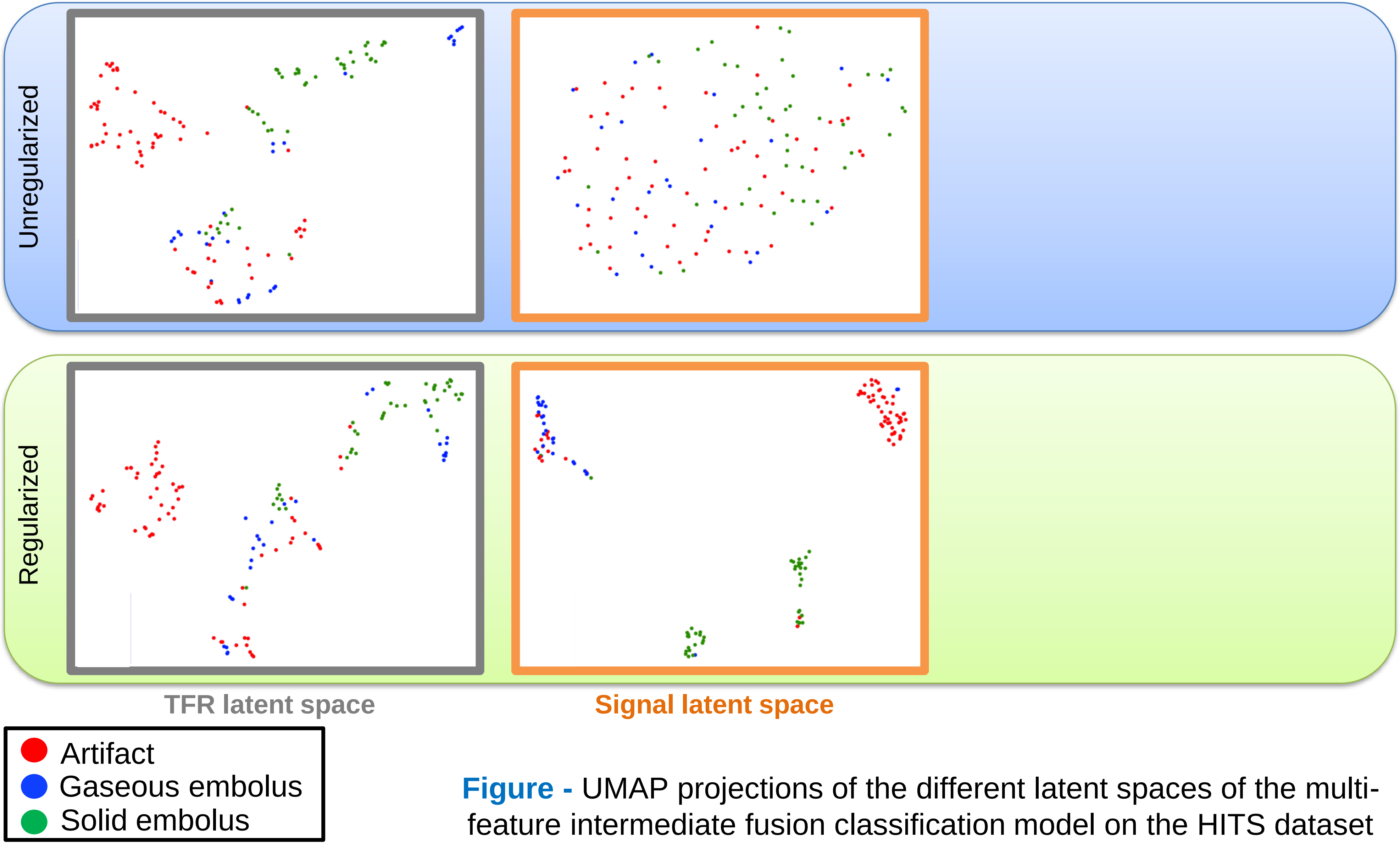


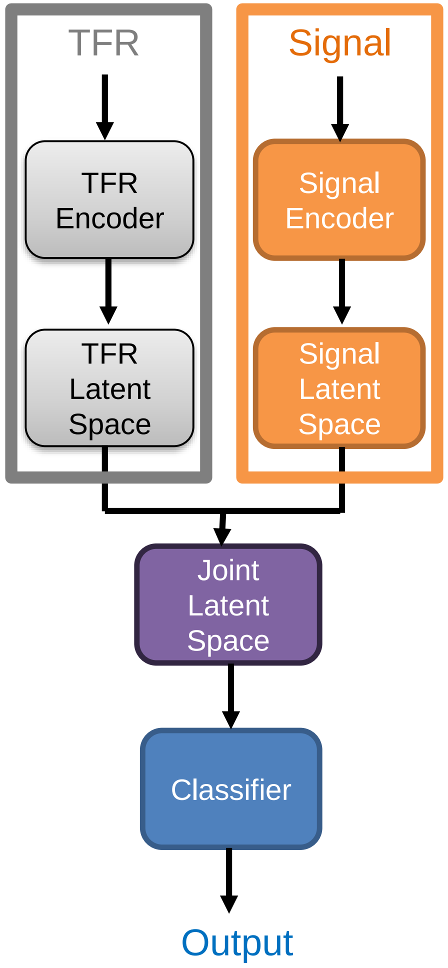


Figure - UMAP projections of the different latent spaces of the multi-feature intermediate fusion classification model on the HITS dataset

Results

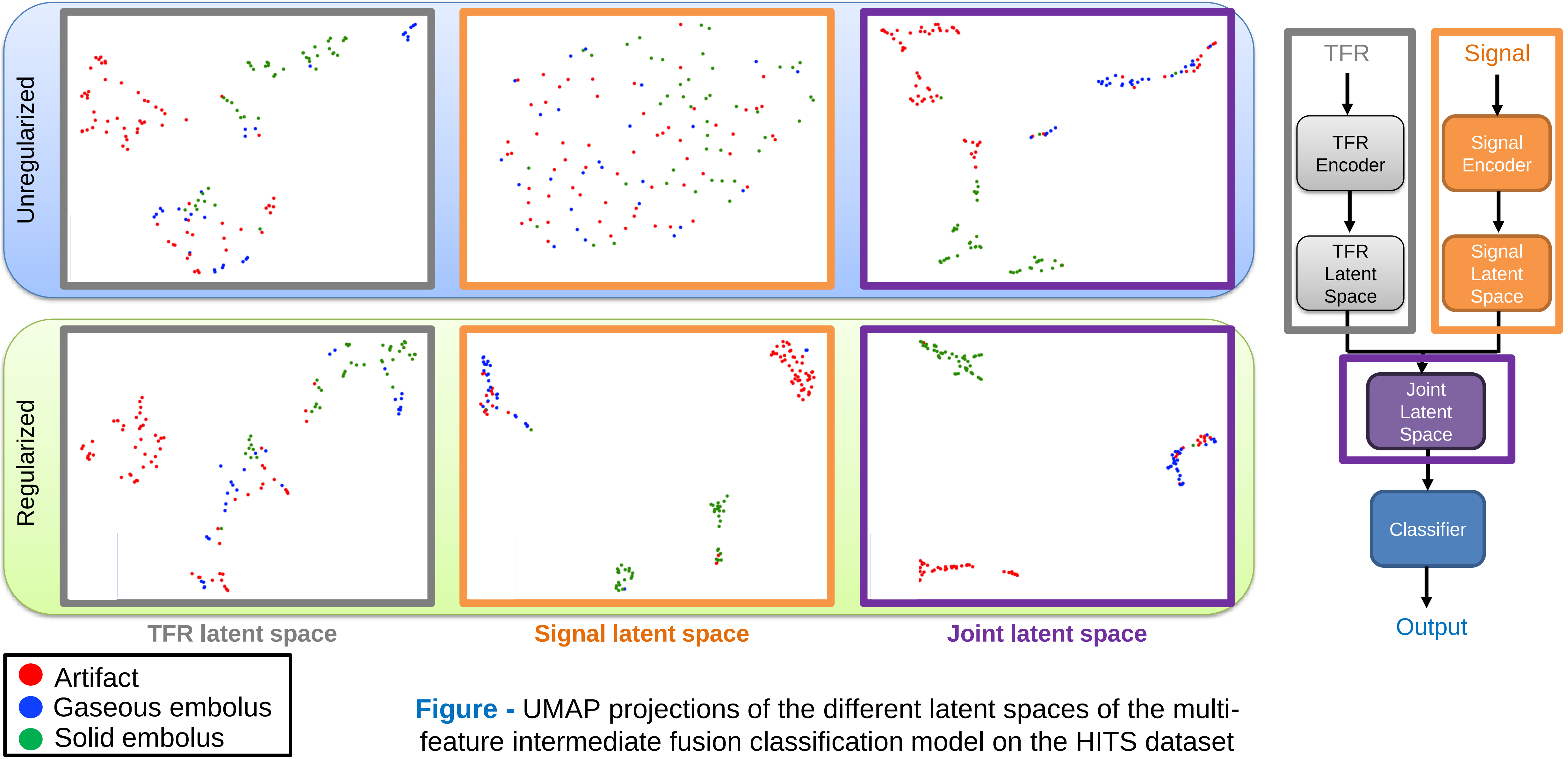


Figure - UMAP projections of the different latent spaces of the multi-feature intermediate fusion classification model on the HITS dataset

Intermediate conclusion

Use of multiple representations of a signal

- TFR and raw signal.
- Two approaches:
  - Late fusion.
  - **Intermediate fusion.**

Intermediate fusion models

- Regularized:
  - **Guided training.**
  - Deep Embedded Clustering (**DEC**).
- End-to-end training.

Results

- **Improvement of HITS classification** performances with **up to +10% MCC**.
- **State-of-the-art results** on other medical signal datasets (EEG and ECG) with up to +4% MCC.

Objectives and Contributions

Dataset creation and annotation →
- Semi-supervised data annotation*
- Soft labelling (annotation)*

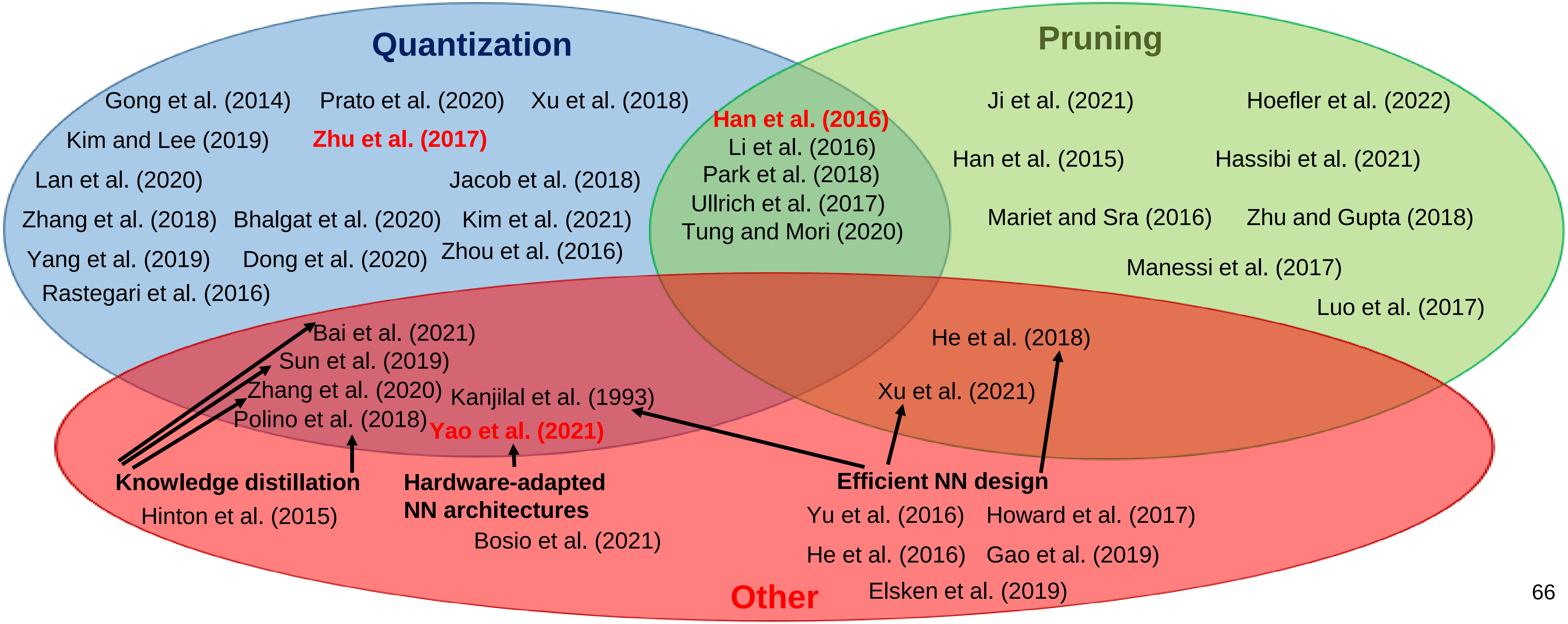
Multiple representations →
- Different models with different inputs**
- Multi-feature models

Resource hungry models →
- Lite models
- Model compression
- (Soft labelling training)

* Vindas et al. (IUS 2021), Vindas et al. (MEDIA 2022), Vindas et al. (IUS 2023)
** Vindas et al. (MLHC 2022), Vindas et al. (IABM 2023), Vindas et al. (EUSIPCO 2023), and Vindas et al. (Pattern Recognition 2023)

Outline

General Overview



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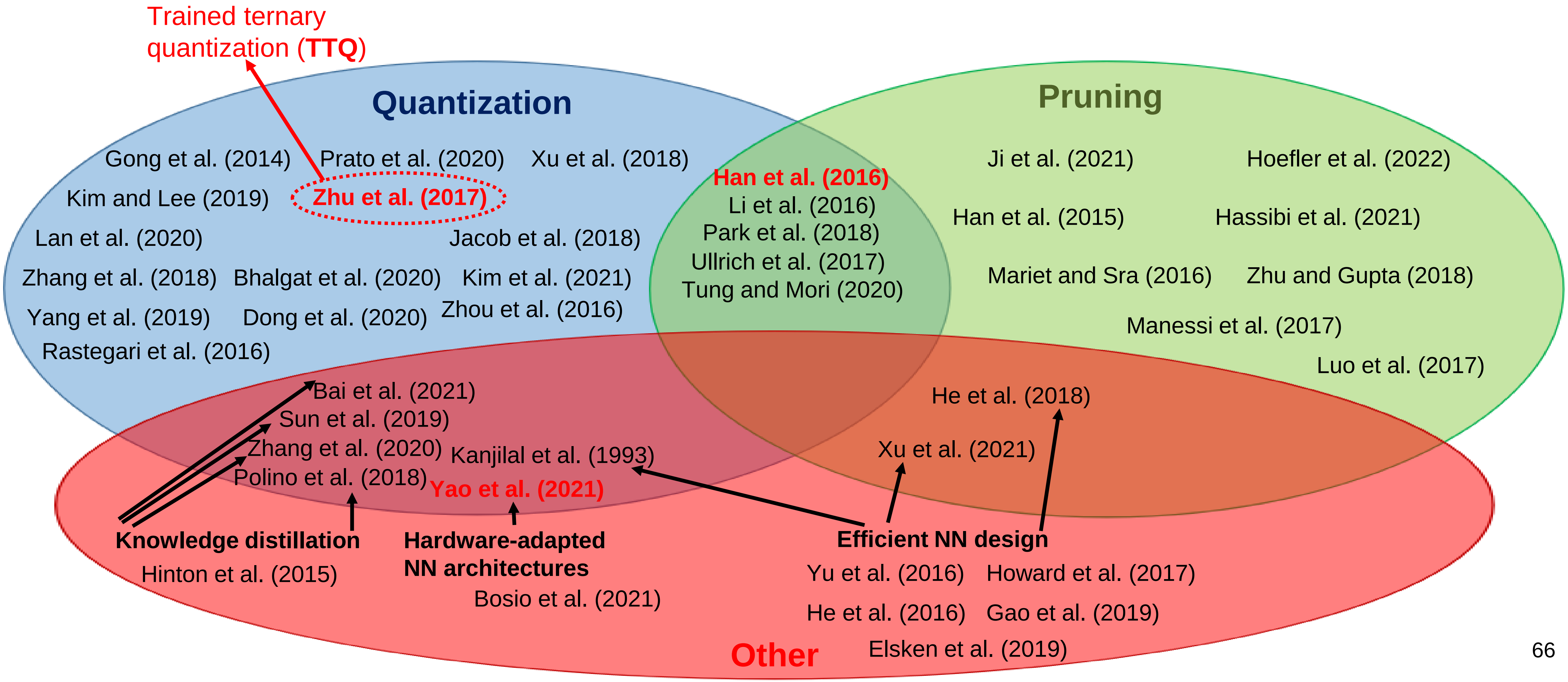

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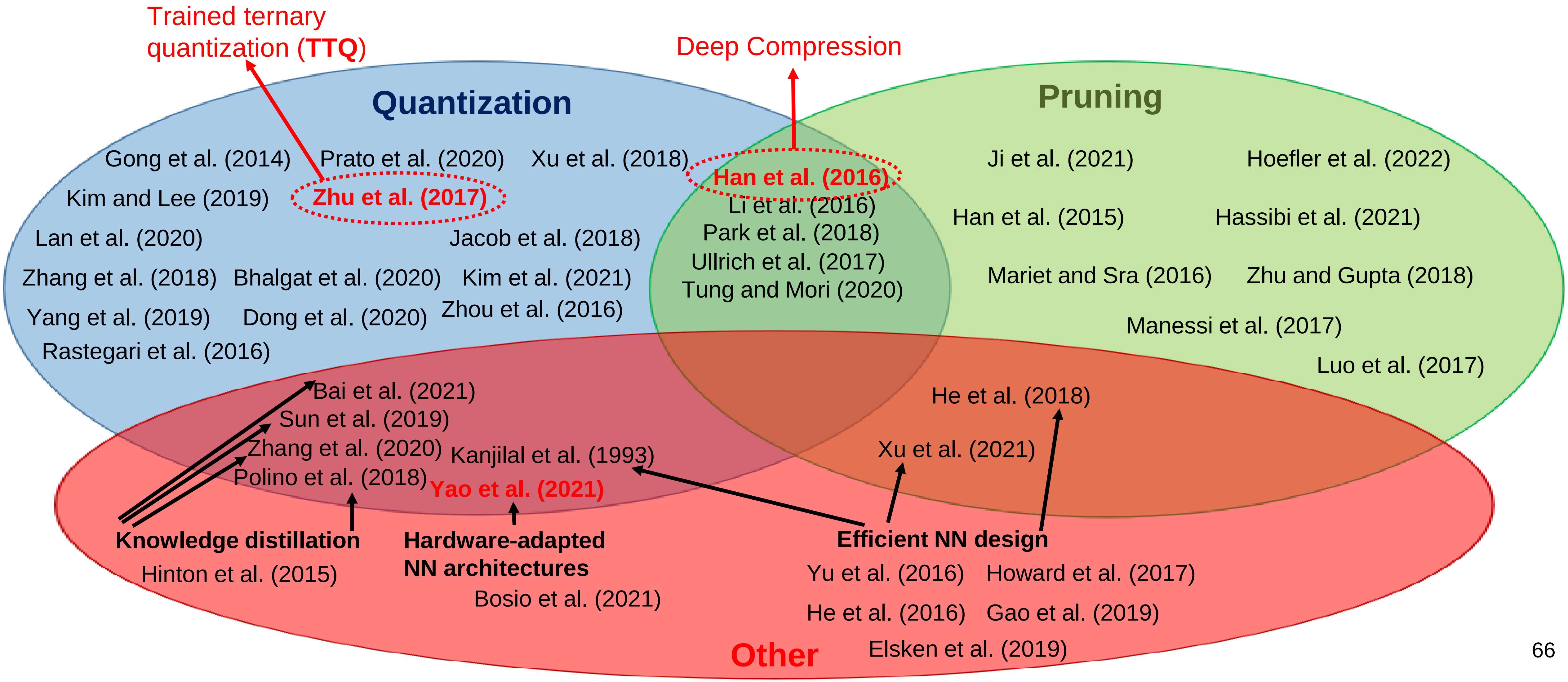

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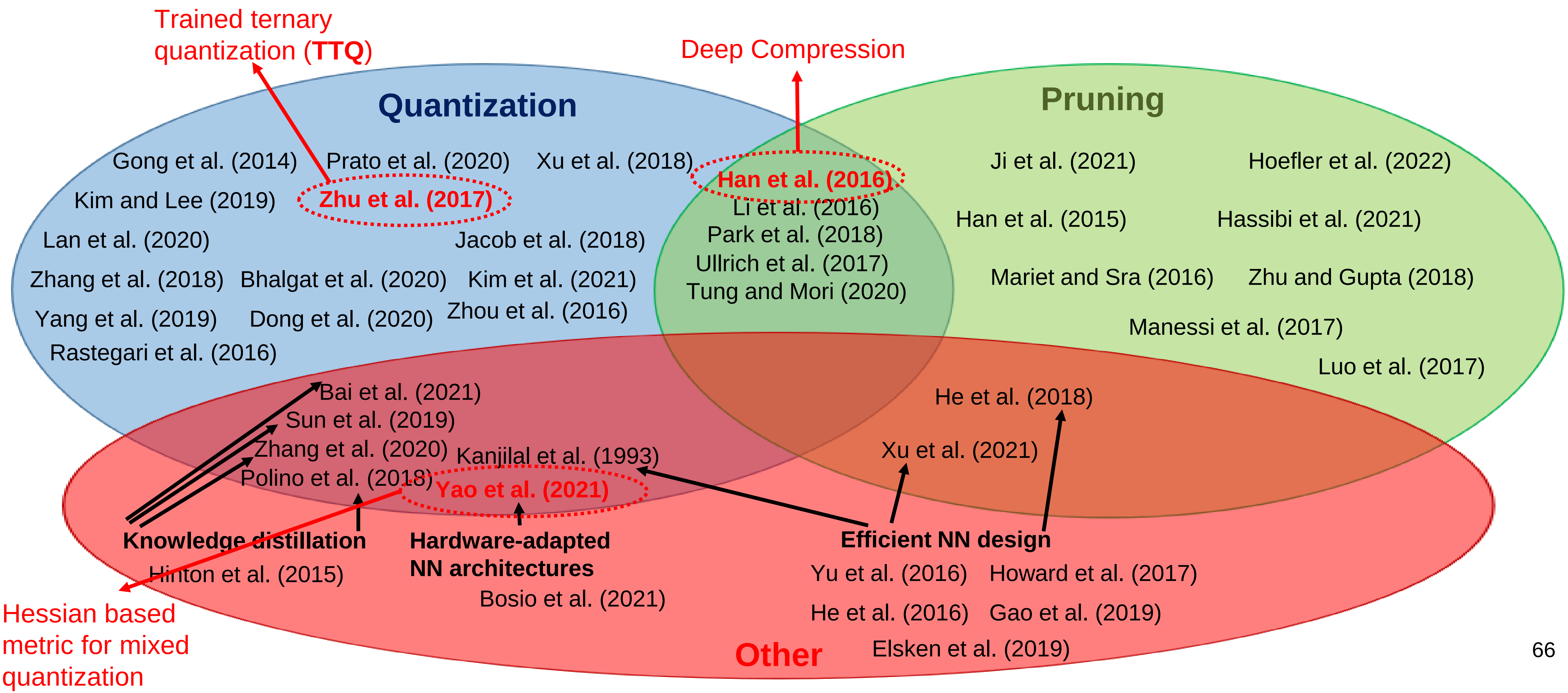

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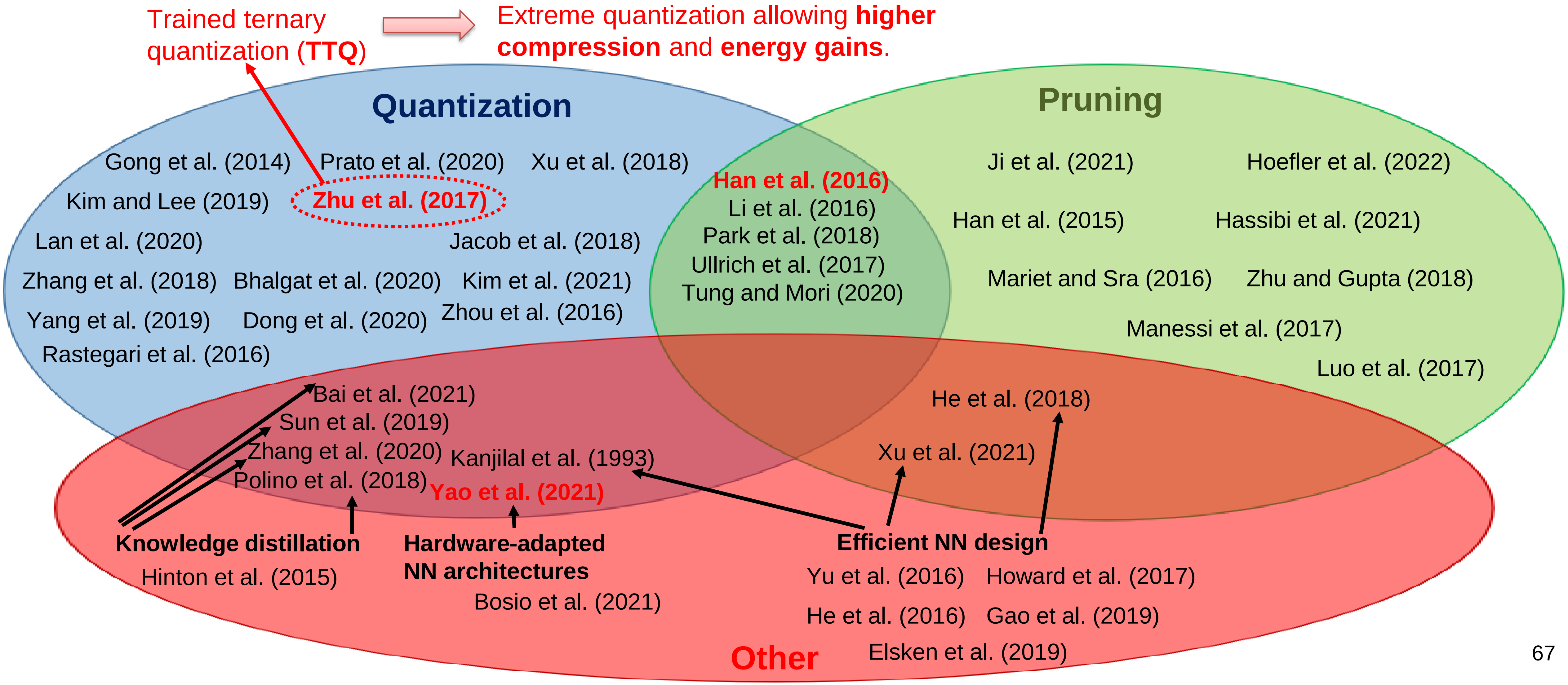
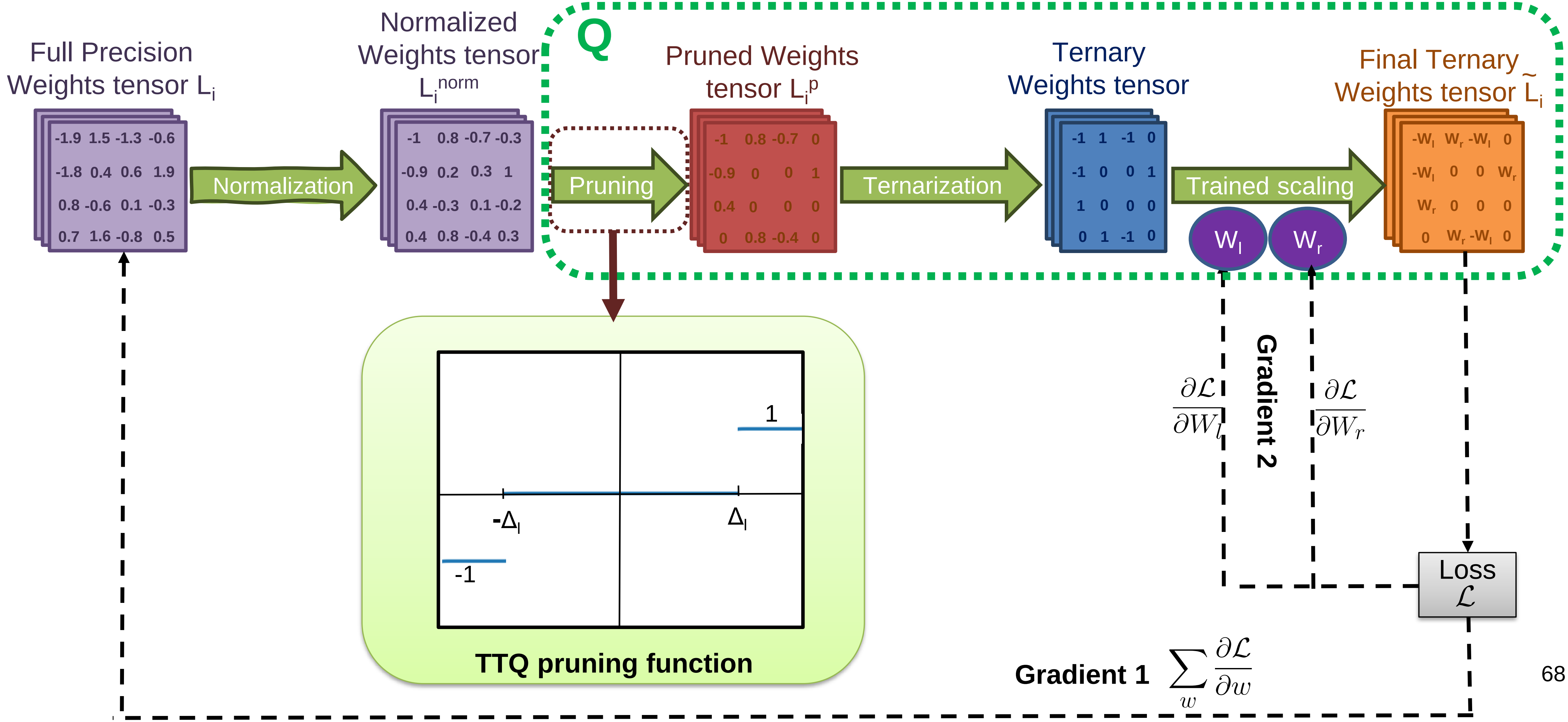


Trained ternary quantization (TTQ) – Zhu et al., 2017



Outline

Claims of contribution 3

a. **Novel ternarization heuristic**, based on the weights' statistics.

b. **Direct asymmetric pruning** before ternarization, allowing a **better trade-off** between compression, energy, and classification.

c. **Asymmetric parametrization** of the sparsity rate, **controlling** the abovementioned **trade-off.**

Global pipeline

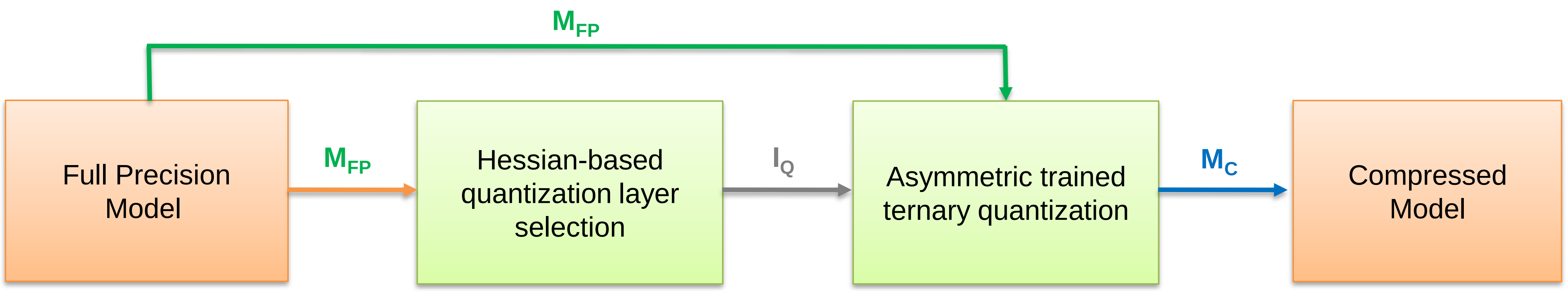
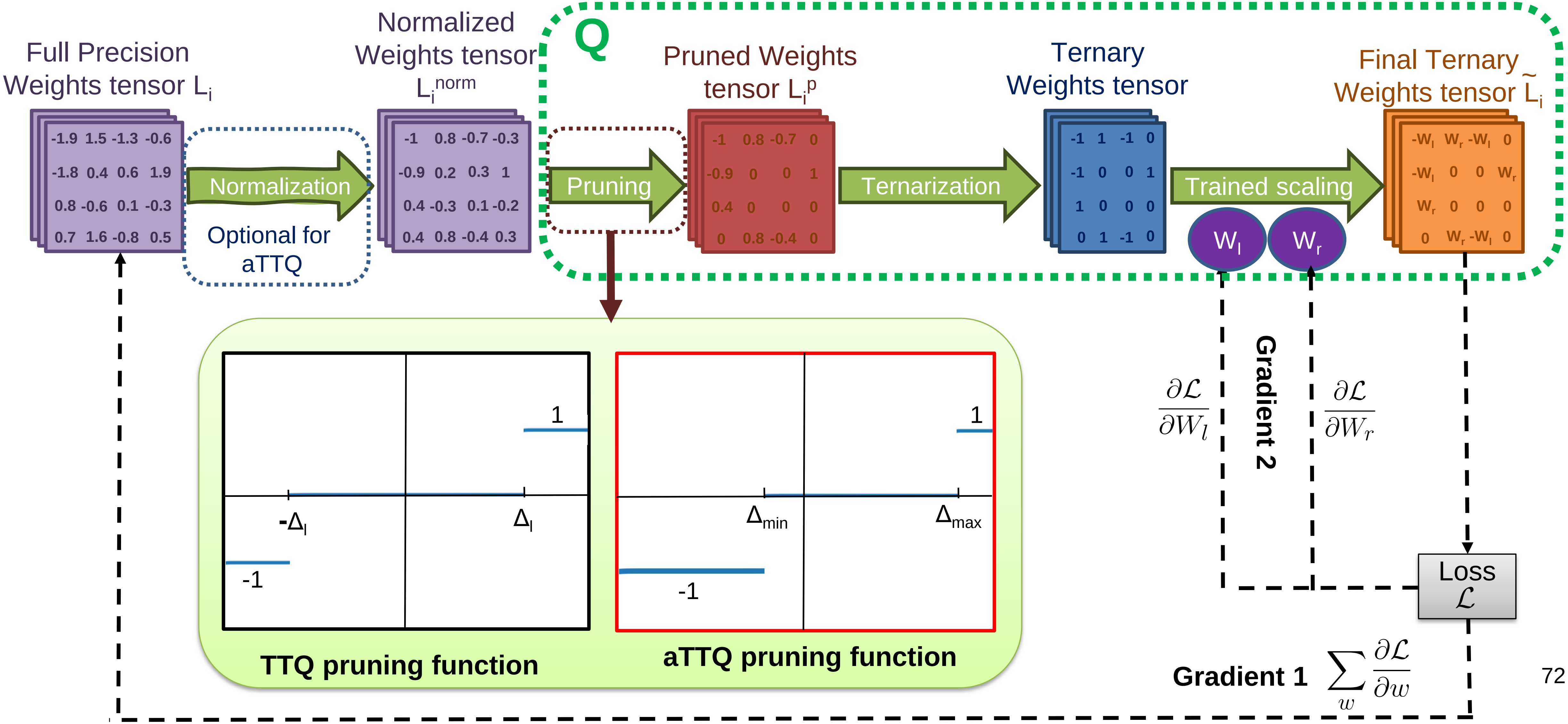


Figure – Global pipeline of our extreme quantization approach.

Asymmetric trained ternary quantization (aTTQ)



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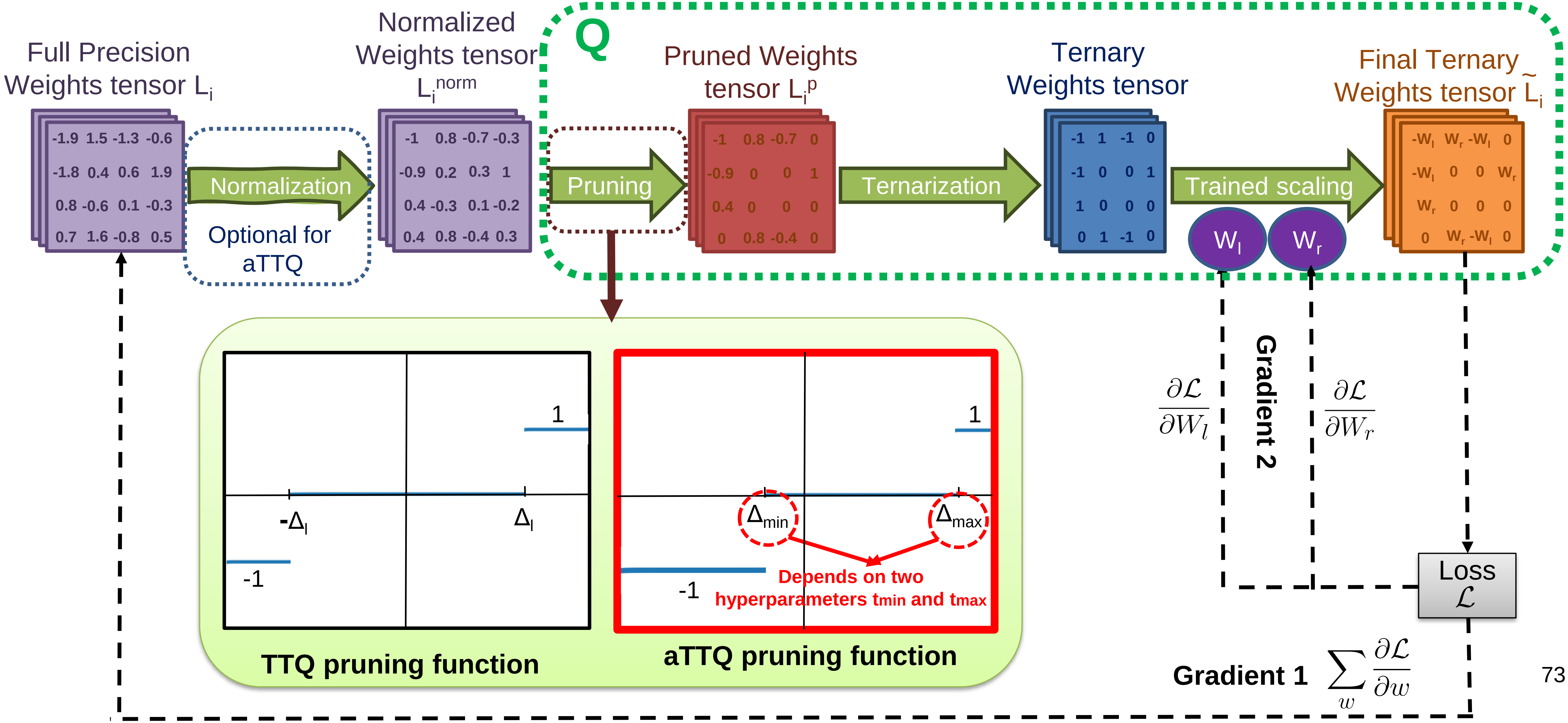

Compression evaluation metrics

Compression-based metrics

$$CR(\mathcal{M}_{FP}, \mathcal{M}_Q) = \frac{nbits(\mathcal{M}_Q)}{nbits(\mathcal{M}_{FP})}$$

$$CR_G(\mathcal{M}_{FP}, \mathcal{M}_Q) = 1 - CR(\mathcal{M}_{FP}, \mathcal{M}_Q)$$

Compression evaluation metrics

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Full precision (FP) model

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Function counting the number of bits necessary to store the weights (using COO sparse storage format)

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The higher the better

Energy evaluation metrics

Energy consumption

$$EC_{Total}(\mathcal{M}) = EC_{MA}(\mathcal{M}) + EC_{DT}(\mathcal{M})$$ in Joules

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The higher the better

Outline

Experiment: SOTA comparison

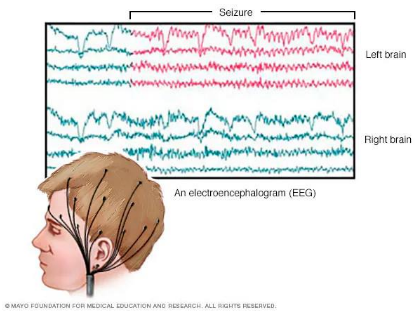
Objective:

- Compare **aTTQ** with other extreme quantization methods: **TTQ**.

Datasets:

HITS:

- TCD Data.
- 1 545 samples.
- Three classes.
- Sampling frequency: 4385 Hz.



ESR:

- EEG Data.
- 11 500 samples.
- Two classes.
- Sampling frequency: 174 Hz.

Metrics:

- ΔMCC, MCC drop with respect to the full precision model.
- Energy consumption gain (EC_G).
- Compression rate gain (CR_G).

Models:

- 2D CNN.
- 1D CNN-transformer.

Loss function:

- Cross entropy (CE)

Experiment: SOTA comparison

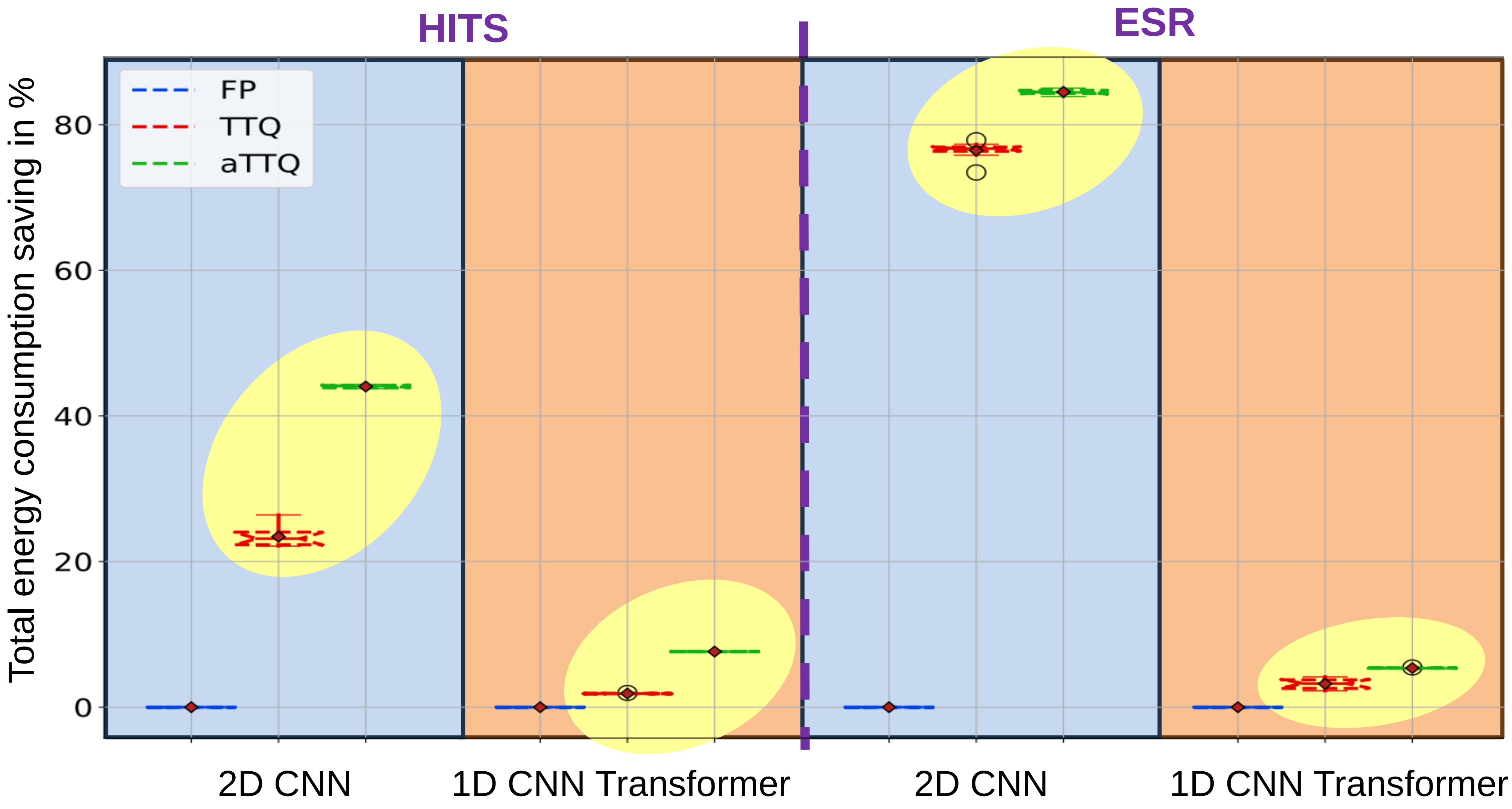


Figure – Comparison of aTTQ with FP and TTQ from the **energy** perspective

Experiment: SOTA comparison

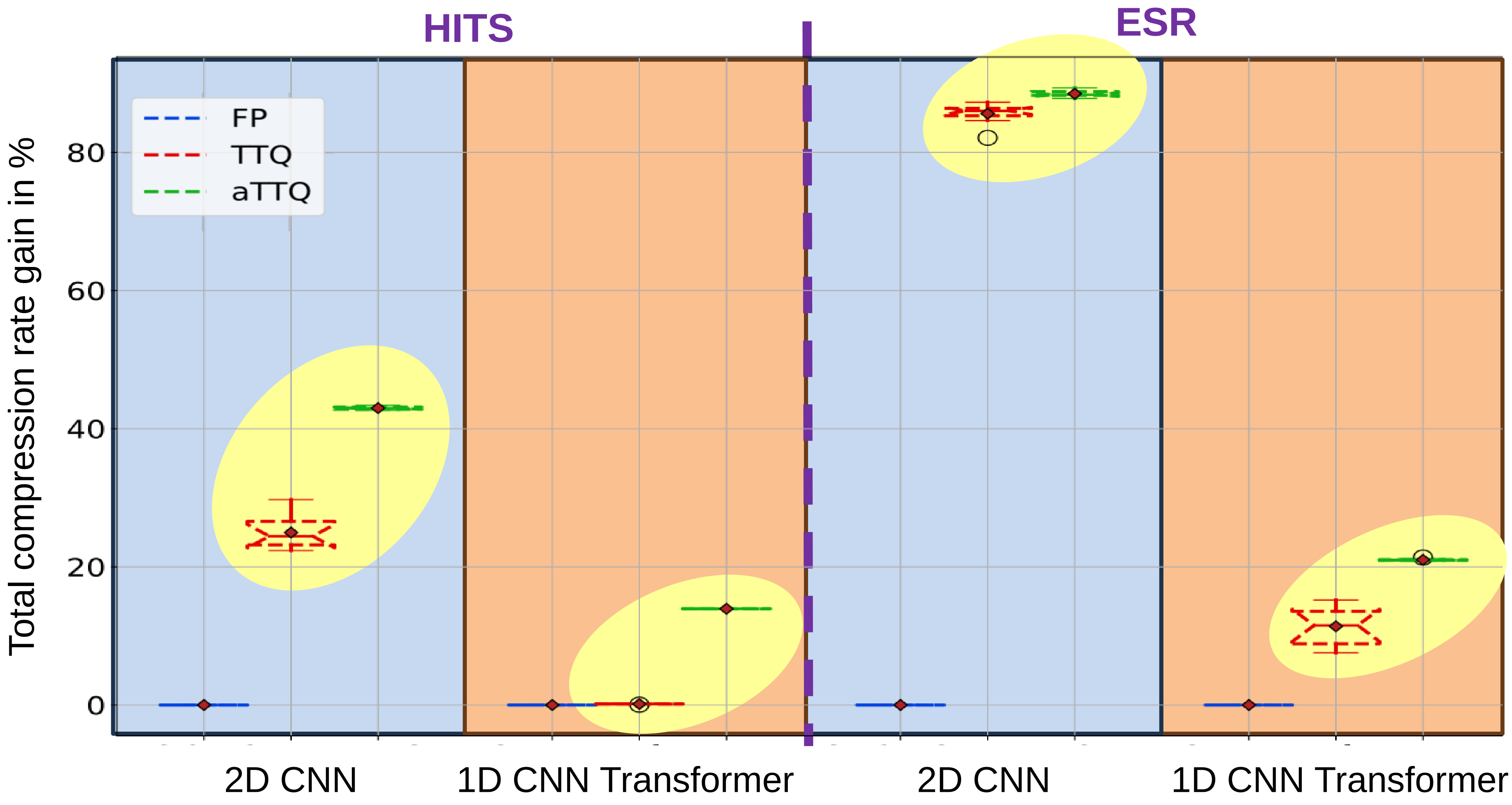


Figure – Comparison of aTTQ with FP and TTQ from the **sparsity/compression** perspective

Experiment: SOTA comparison

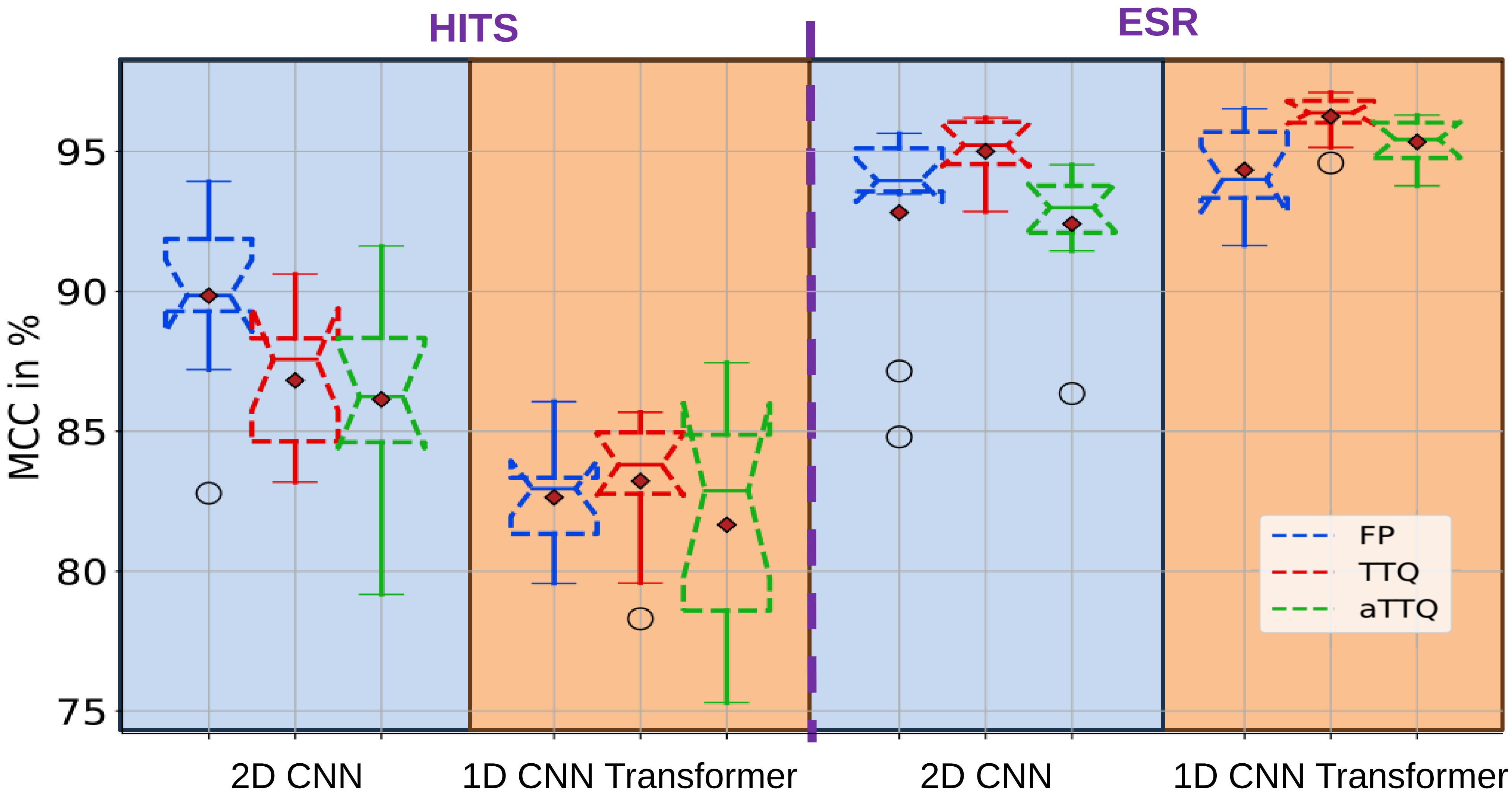
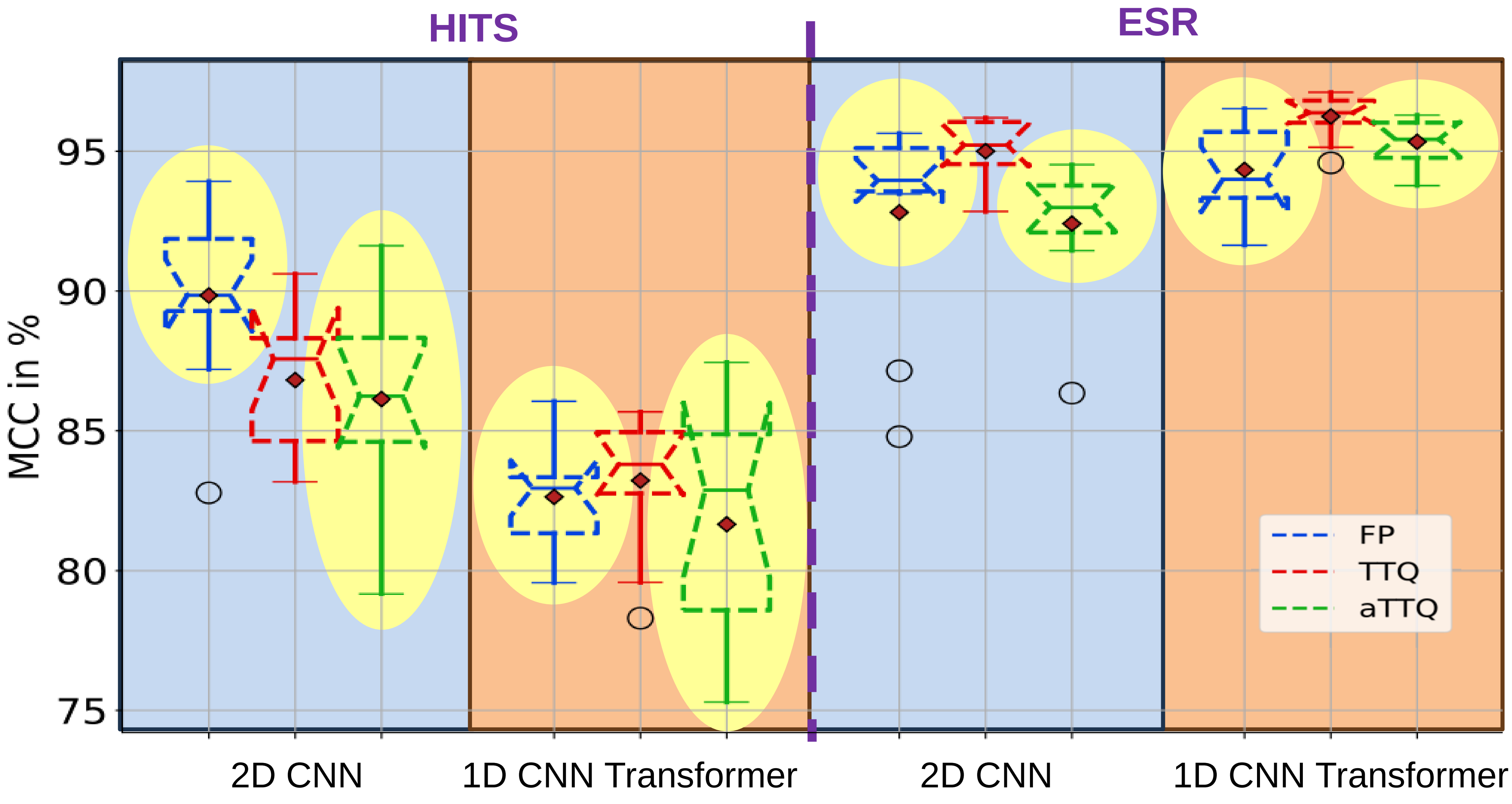


Figure – Comparison of aTTQ with FP and TTQ from the **classification** perspective

Experiment: SOTA comparison



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Experiment: SOTA comparison

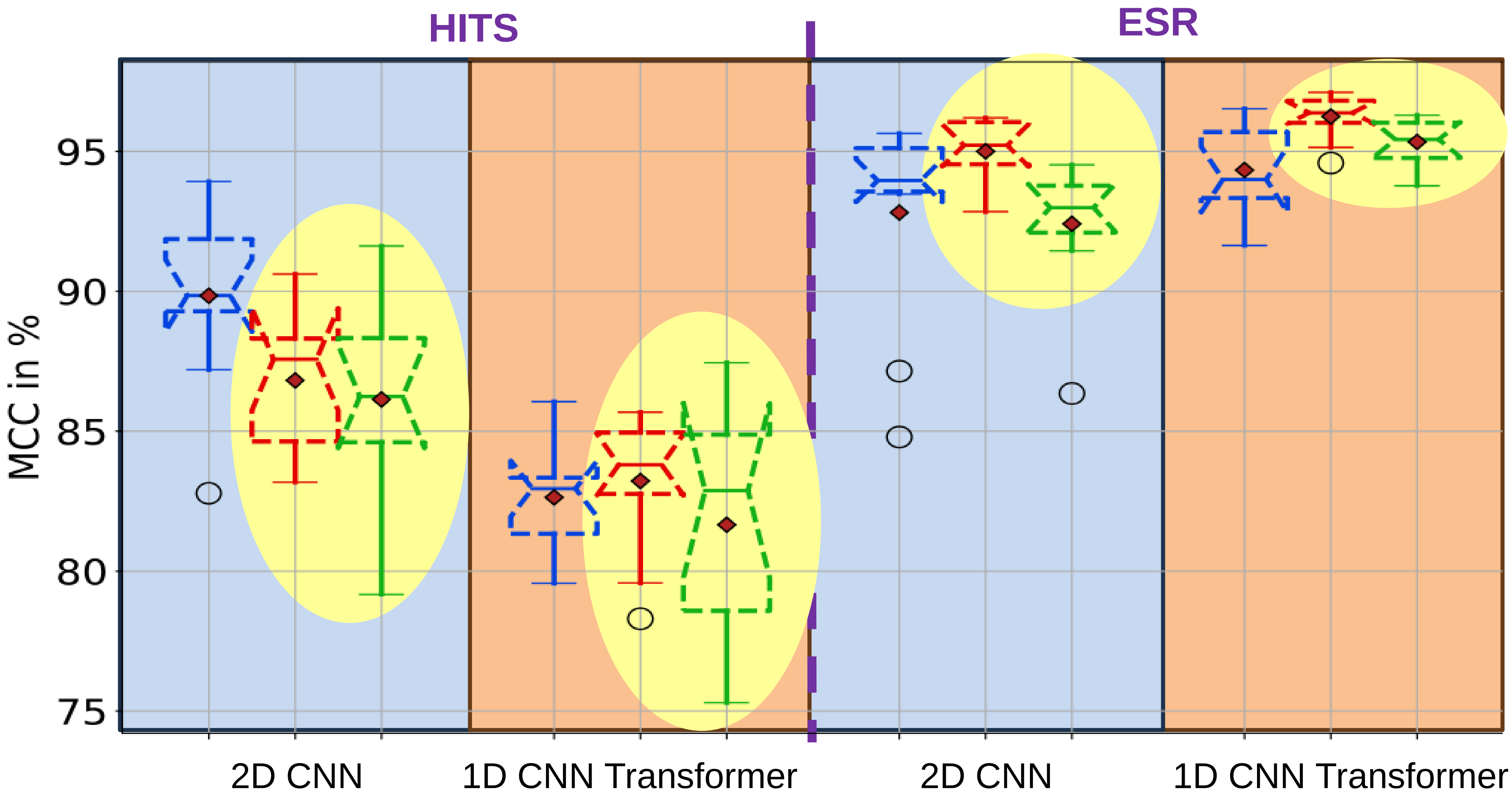

Figure – Comparison of aTTQ with FP and TTQ from the **classification** perspective

Intermediate conclusion

- **Novel ternarization method:**
  - Pruning based on the weights' statistics.
  - Parametrization to control the compression/energy/classification trade-off

- **Better compression/classification trade-off:**
  - **Improvement up to 14% CR_G** in terms of compression and **6% EC_G^T** in terms of energy **w.r.t TTQ**.
  - For a **degradation** of **only 1.6%** in terms of **MCC** on the **HITS** dataset.

- **Two hyperparameters controlling this trade-off:**
  - The larger the gap:
    - The higher the compression performance.
    - The smaller the classification performance.

Outline

Conclusion

Before	After

Conclusion

Before	**After**
Portable TCD dataset with **2%** of **hard-labeled** samples	

Conclusion

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Portable TCD dataset with **2%** of **hard-labeled** samples	• **12 %** of **soft-labeled** samples • **App prototype** for semi-automatic data annotation.

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Emboli vs artifact classification using **time-frequency** representations	• **Solid embolus vs gaseous embolus vs artifact** classification. • Single and **multi-feature models transferred** to **Atys** Medical**.**
Resource and **energy hungry** models	• **Compressed** sparse and ternary **single feature models.**

Perspectives

Perspectives

Dataset creation and annotation

Perspectives

Dataset creation and annotation

Active learning by proposing to human experts the most difficult samples.

Use **soft annotations** through **soft-lables loss functions*** to capture the human expert uncertainty.

* Vindas, Y., Roux, E., Guépié, B.K., Almar, M., Delachartre, P., 2023. Soft-labels noise tolerant loss functions for transcranial Doppler ultrasound signal classification, in: 2023 IEEE International Ultrasonics Symposium (IUS)

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Dataset creation and annotation → **Active learning** by proposing to human experts the most difficult samples.

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Multiple representations → Use **other** types of **regularization** (contrastive learning with weak supervision, link constraints, …).

Resource hungry models → **Differentiable pruning function**, with asymmetric learnable parameters.

* Vindas, Y., Roux, E., Guépié, B.K., Almar, M., Delachartre, P., 2023. Soft-labels noise tolerant loss functions for transcranial Doppler ultrasound signal classification, in: 2023 IEEE International Ultrasonics Symposium (IUS)

Publications

Journals:

- **Vindas, Y.**, Guépié, B.K., Almar, M., Roux, E., and Delachartre, P., 2022. Semi-automatic data annotation based on feature-space projection and local quality metrics: an application to cerebral emboli characterization, in **Medical Image Analysis**, page 102437, 2022. ISSN 1361-8415. doi: https://doi.org/10.1016/j.media.2022.102437.

- **Vindas, Y.**, Roux, E., Guépié, B.K., Almar, M., Delachartre, P., 2023 Guided Deep Embedded Clustering regularization for multi-feature medical signal classification, **Pattern Recognition**, page 109812, 2023. ISSN 0031-3203. https://doi.org/10.1016/j.patcog.2023.109812.

Conferences with proceeding:

- **Vindas, Y.**, Roux, E., Guépié, B.K., Almar, M., Delachartre, P., 2021. Semi-supervised annotation of transcranial Doppler ultrasound micro-embolic data, in: 2021 IEEE International Ultrasonics Symposium (**IUS**), pp. 1–4. doi:10.1109/IUS52206.2021.9593847.

- **Vindas, Y.**, Guépié, B.K., Almar, M., Roux, E., and Delachartre, P., 2022. An hybrid CNN-Transformer model based on multi-feature extraction and attention fusion mechanism for cerebral emboli classification, in: **MLHC**. 05–06 Aug 2022, PMLR.

- **Vindas, Y.**, Roux, E., Guépié, B.K., Almar, M., Delachartre, P., 2023 Deep Embedded Clustering regularization for imbalanced cerebral emboli classification using transcranial Doppler ultrasound, in: European Signal Processing Conference (**EUSIPCO**) 04-08 Sep 2023

- **Vindas, Y.**, Roux, E., Guépié, B.K., Almar, M., Delachartre, P., 2023. Soft-labels noise tolerant loss functions for transcranial Doppler ultrasound signal classification, in: 2023 IEEE International Ultrasonics Symposium (**IUS**)

Conferences without proceeding:

- **Vindas, Y.**, Guépié, B.K., Almar, M., Roux, E., and Delachartre, P., 2023. Classification multi-représentation d'emboles cérébraux à partir d'un dispositif de Doppler transcrânien. in:2023 Intelligence Artificielle en Imagerie Biomédicale (**IABM**).

Submitted/In Progress works:

- **Vindas, Y.**, Roux, E., Guépié, B.K., Almar, M., Delachartre, P., 2023. An asymmetric heuristic for trained ternary quantization based on the weights' statistics: an application to medical signal classification. **Submitted** to *Pattern Recognition Letters*.

- **Vindas, Y.**, Guépié, B.K., Almar, M., Roux, E., and Delachartre, P., 2023. Pruned trained ternary quantization. **In Progress** to *Information Sciences*.

Thank you for your attention

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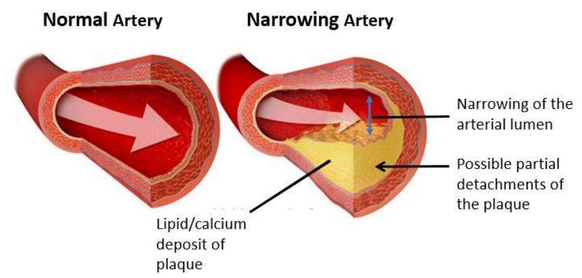
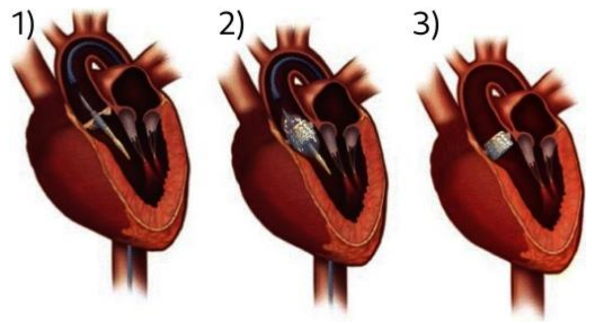
Backslides

Context

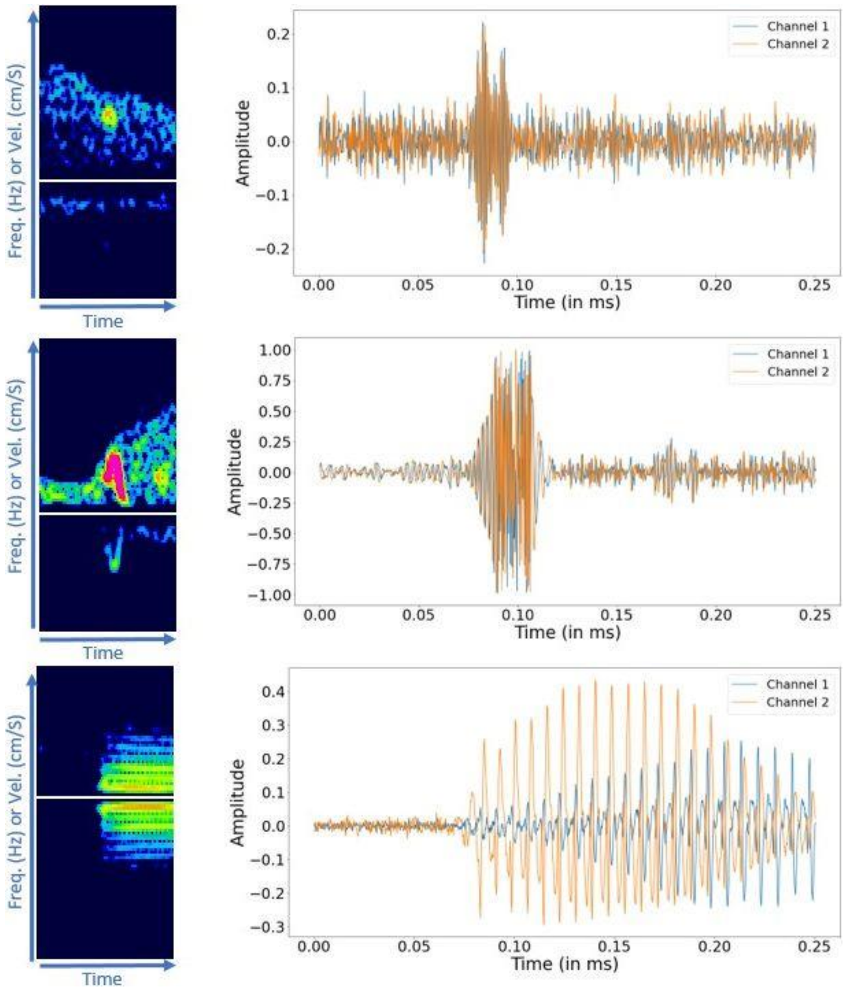
WHY ?

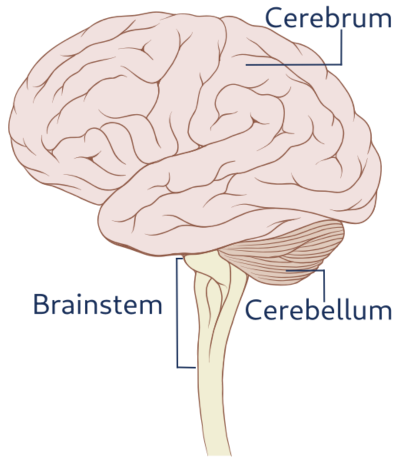


Atherosclerosis



Transcatheter aortic valve replacement



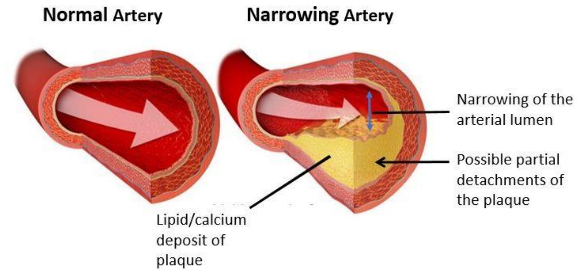


Different Sources

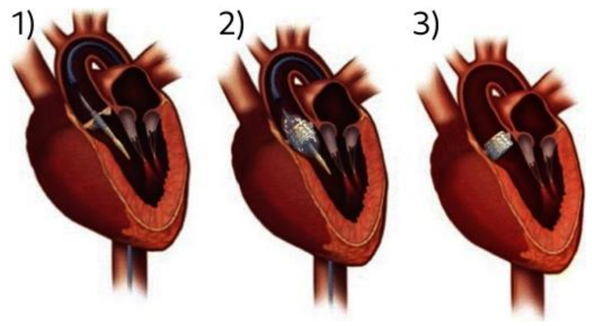
Different Types

Different Consequences

WHY ?

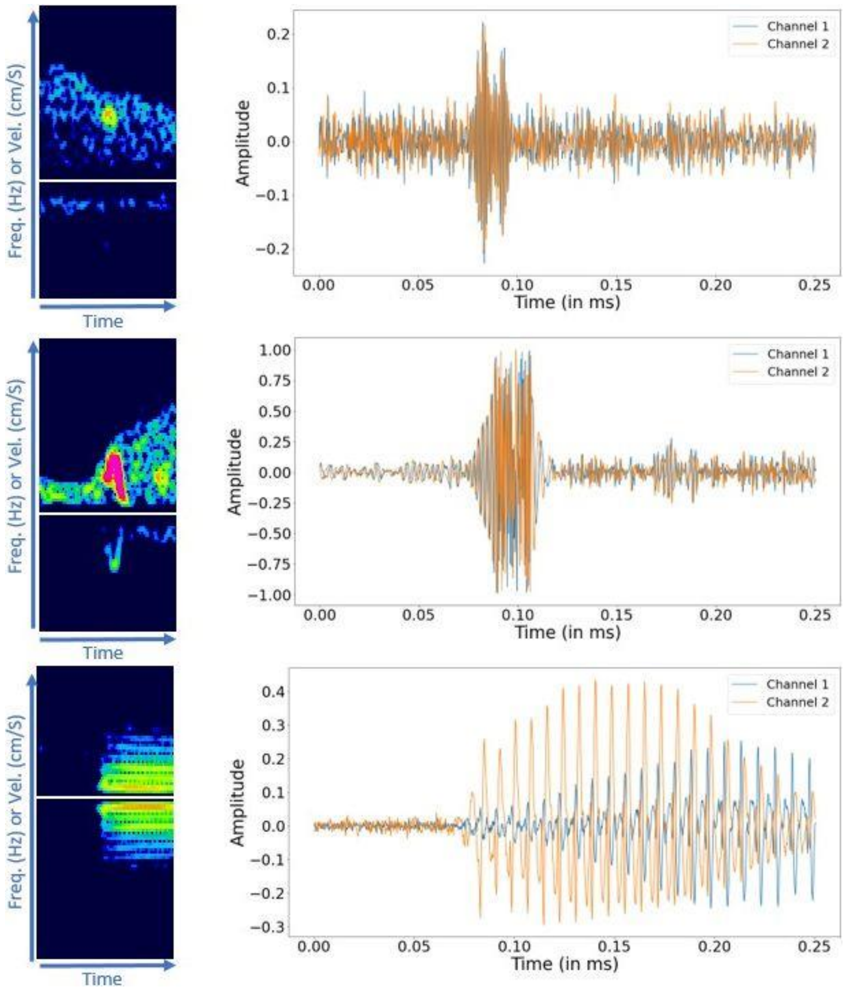


Atherosclerosis

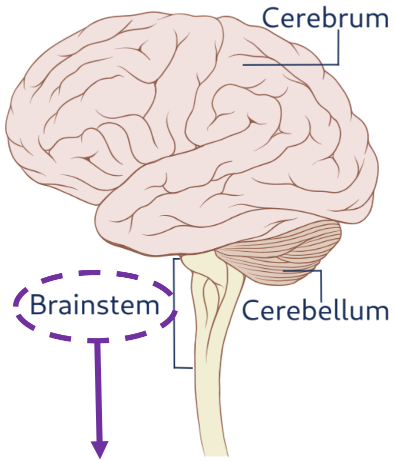


Transcatheter aortic valve replacement

Different Sources



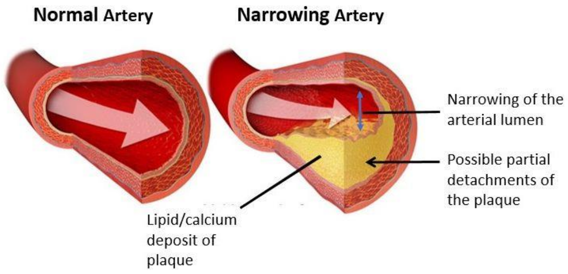
Different Types



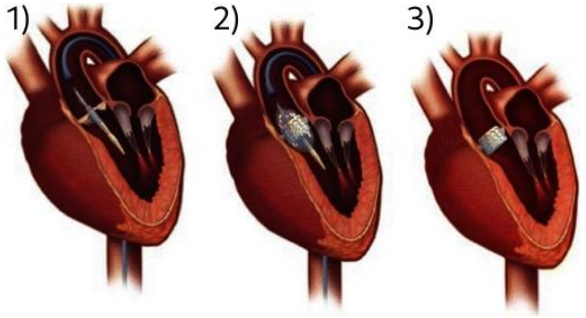
- Temperature regulation.
- Heart rate and blood pressure.
- Vision.
- Balance and coordination.
- Swallowing.
- Coma or death.

Different Consequences

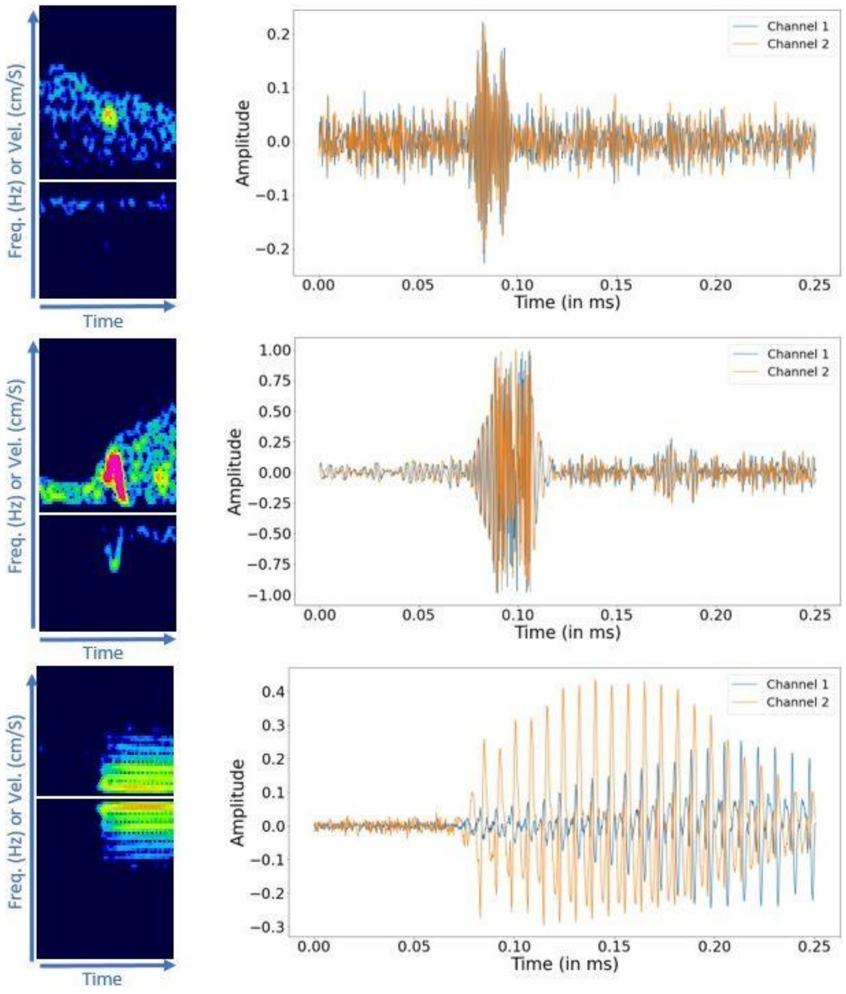
WHY ?

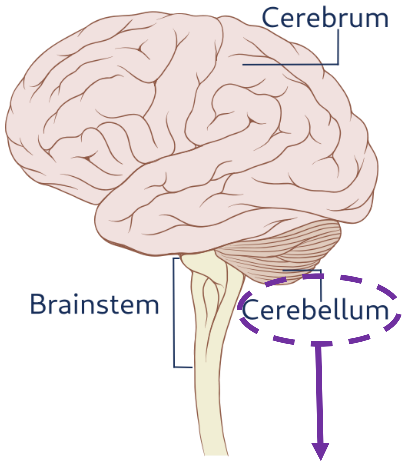


Atherosclerosis



Transcatheter aortic valve replacement





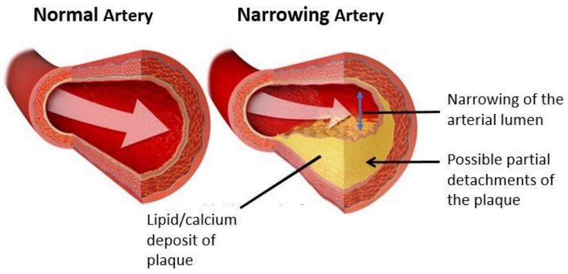
- Balance and posture.
- Muscle movements.
- Headache.
- Nausea.

Different Sources

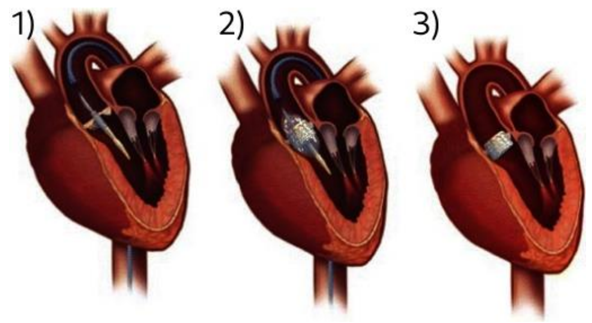
Different Types

Different Consequences

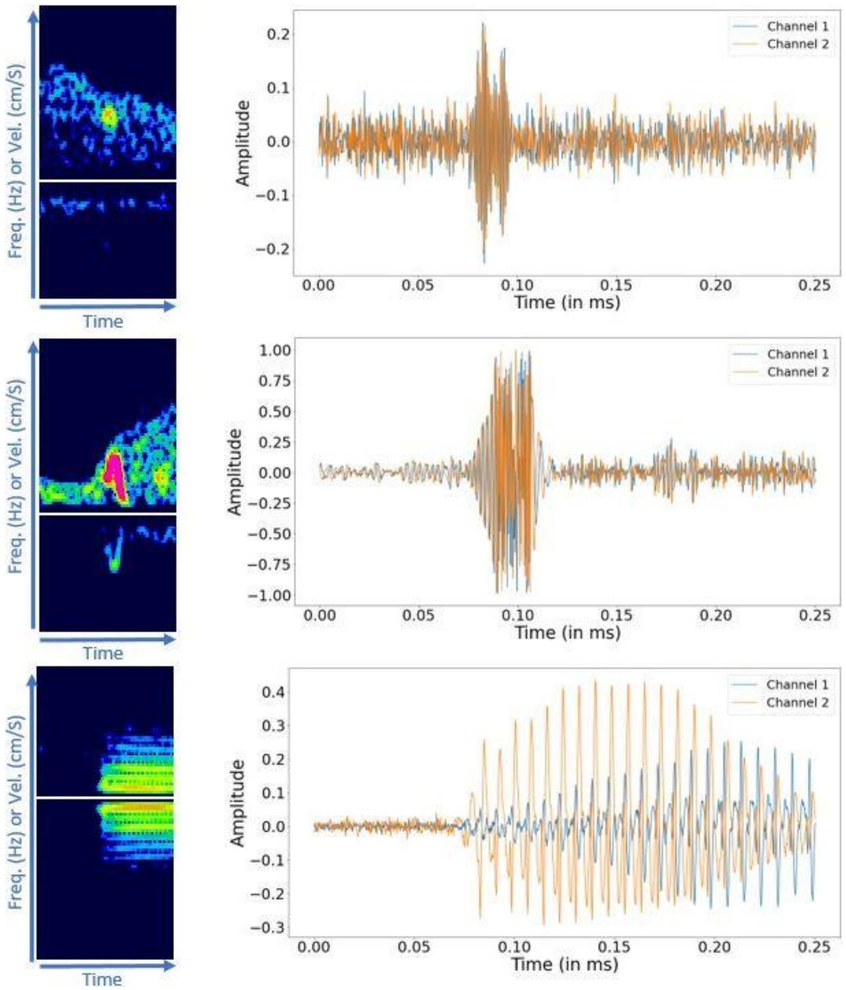
WHY ?



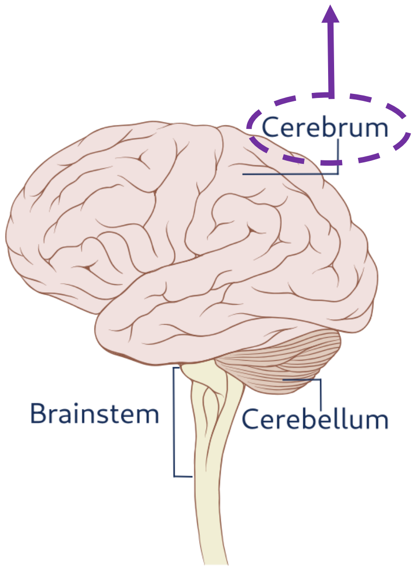
Atherosclerosis



Transcatheter aortic valve replacement



- Memory.
- Reasoning.
- Paralysis.
- Vision and speech.
- Behavior.

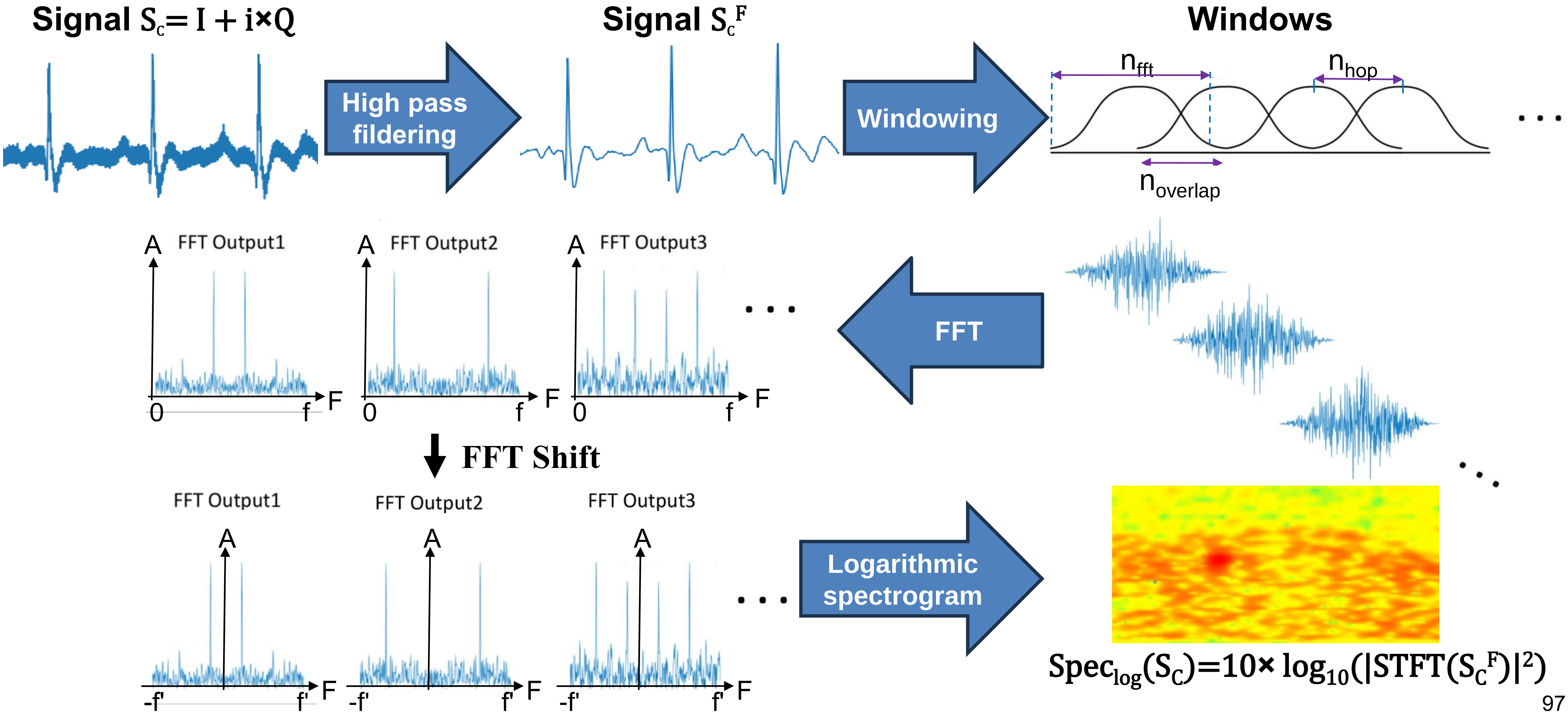


Different Sources

Different Types

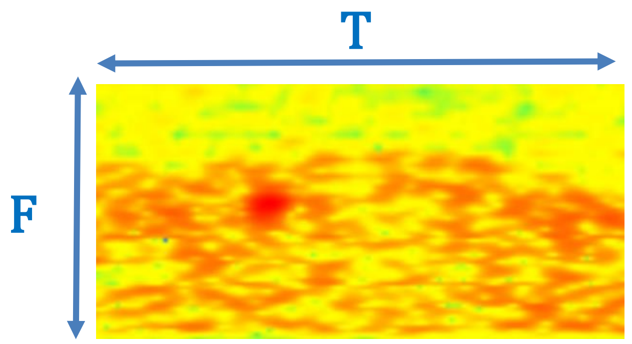
Different Consequences

Time-frequency representations



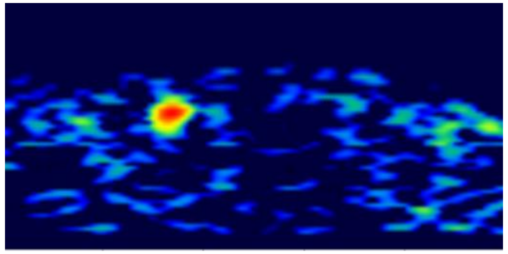
$$Spec_{log}(S_C) = 10 \times \log_{10}(|STFT(S_C^F)|^2)$$

Time-frequency representations



$$Spec_{log}(S_C)=10\times \log_{10}(|STFT(S_C^F)|^2)$$

Filtering



$$Spec_{final}(S_C)=Filter(Spec_{log}(S_C))$$

$$\forall i\in[1,F],\ j\in[1,F],\ Spec_{final}(S_C) = \begin{cases} min_{dB} \text{ if } Spec_{log}(S_C)[i,j] < min_{dB}=\mu_{Spec}+a\times\sigma_{Spec} \\ Spec_{log}(S_C)[i,j] \text{ if } Spec_{log}(S_C)[i,j] \in [min_{dB}, max_{dB}] \\ max_{dB} \text{ if } Spec_{log}(S_C)[i,j] > max_{dB}=\mu_{Spec}+b\times\sigma_{Spec} \end{cases}$$

Emboli detection

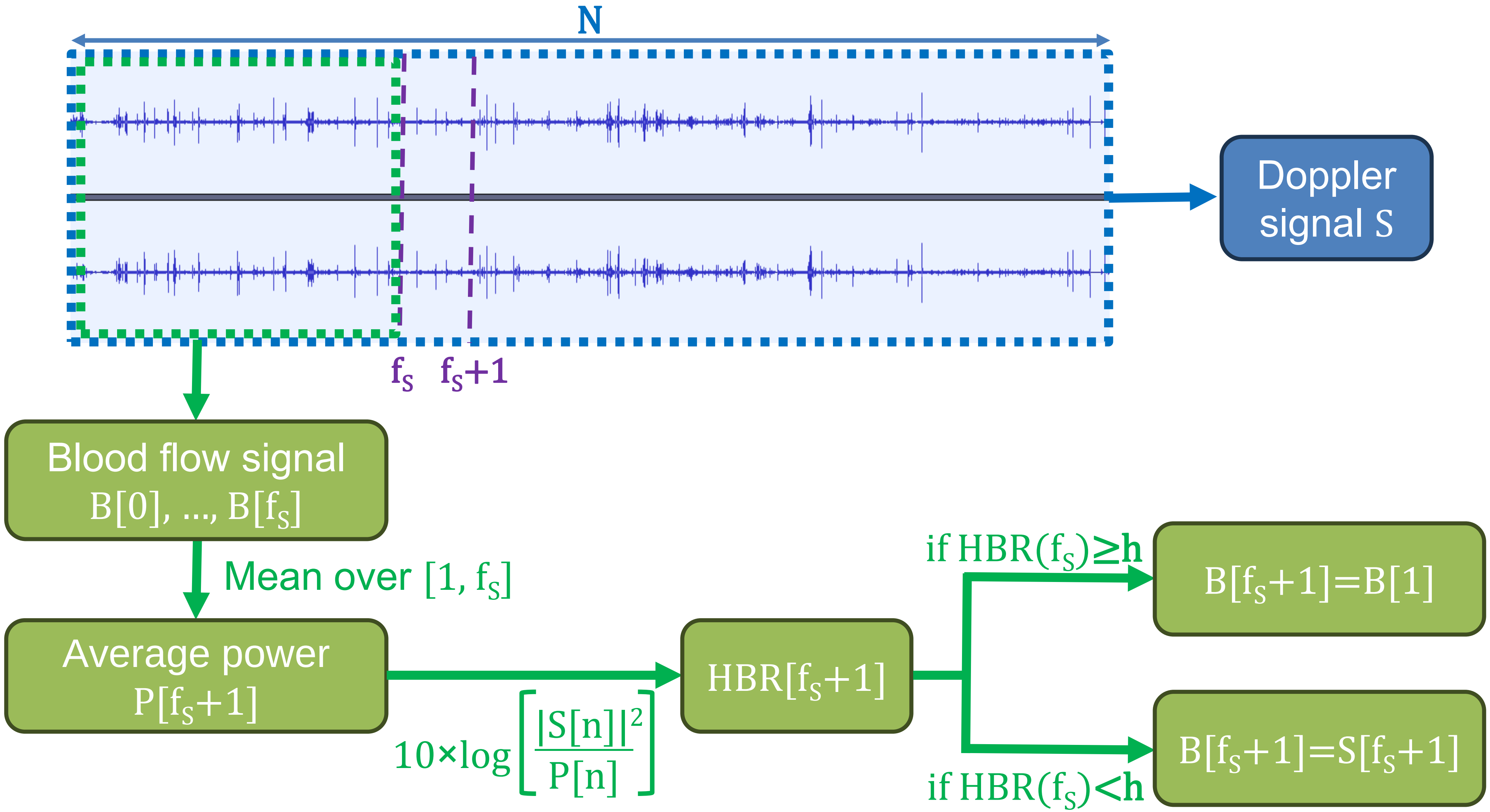


Figure – HBR computation **initialization** from Guépié et al. (2019)

Emboli detection

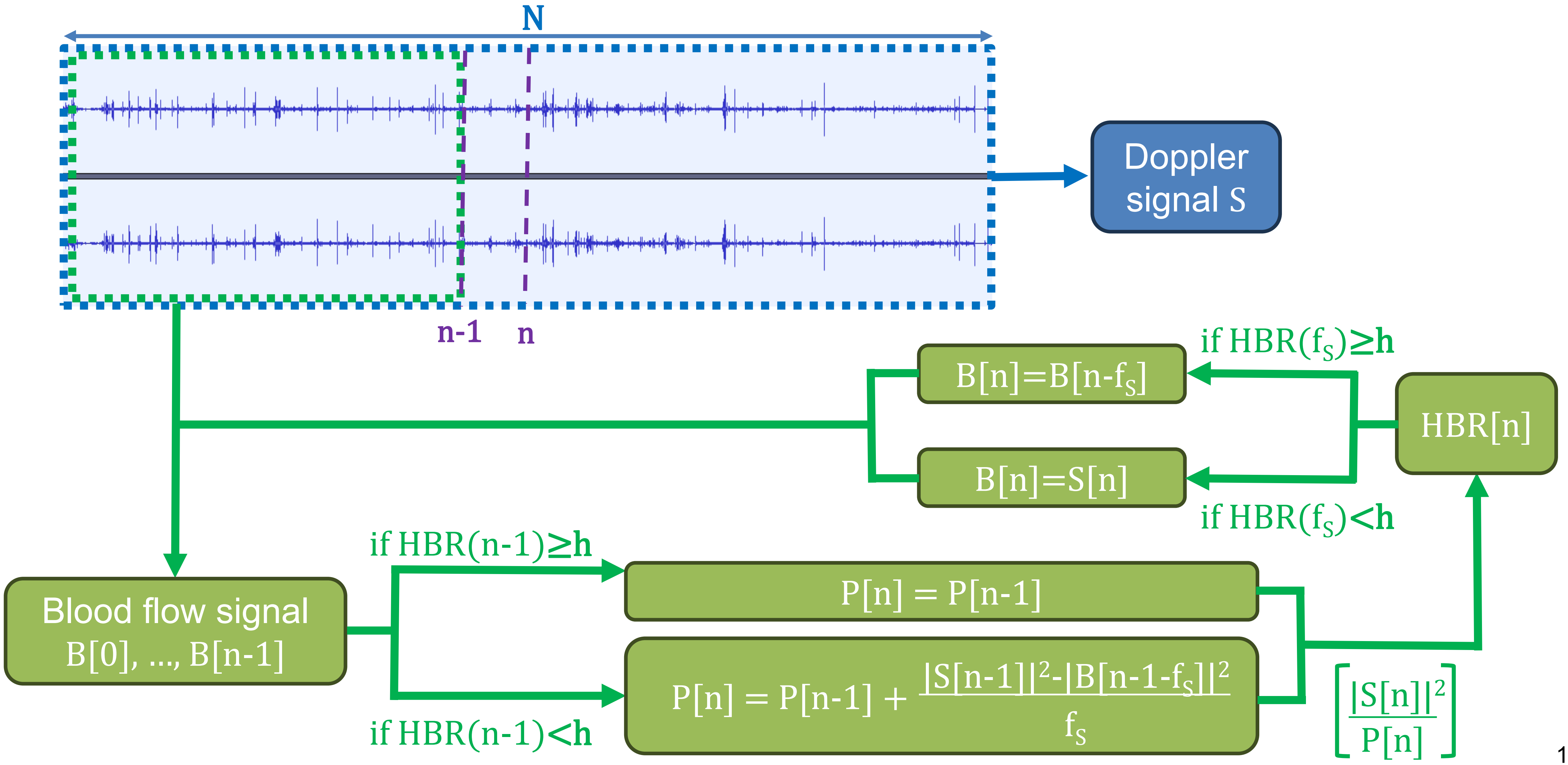
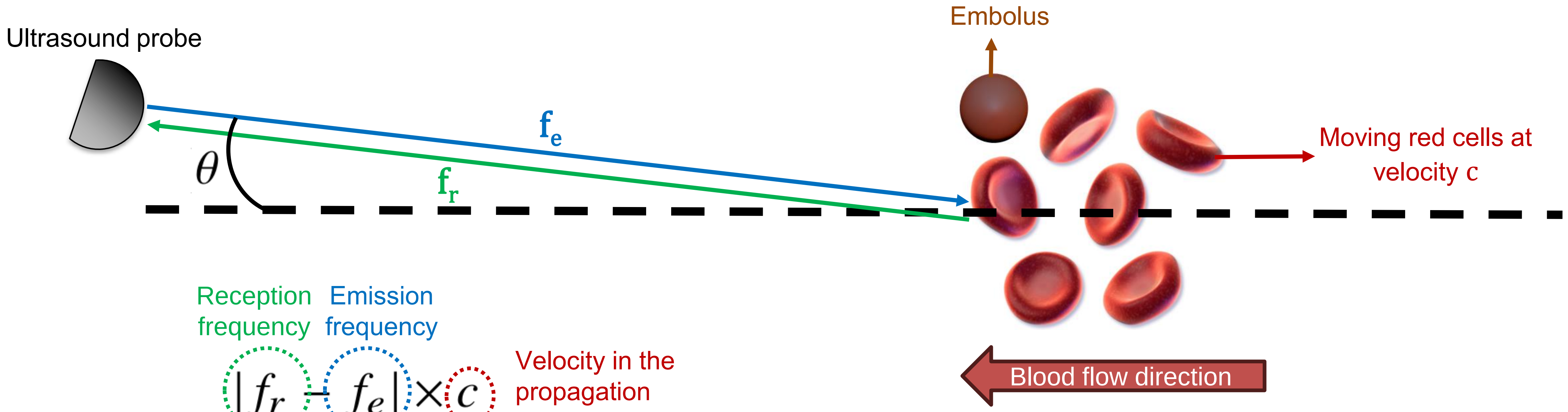


Figure – HBR computation **iteration** from Guépié et al. (2019)

Transcranial Doppler ultrasonography



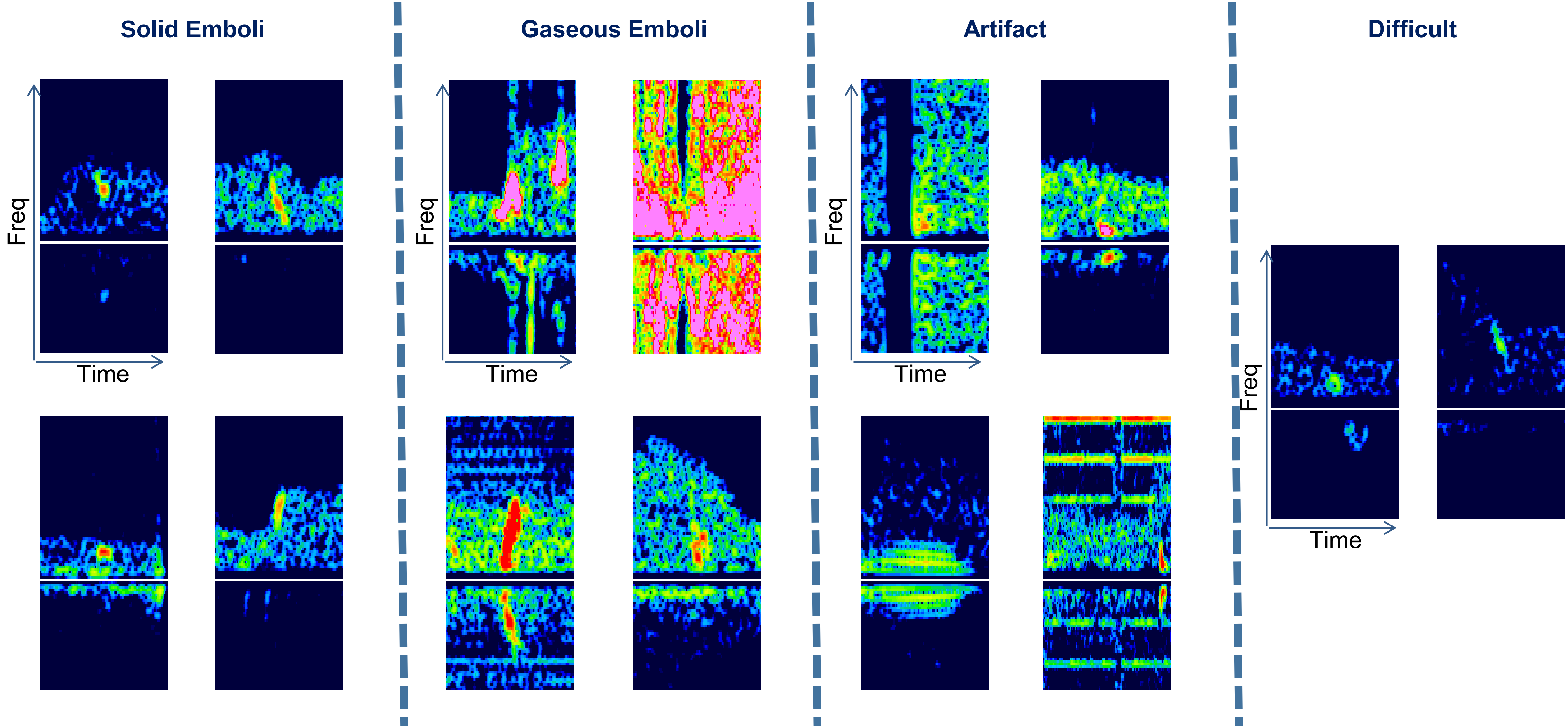
Reception frequency Emission frequency

Velocity in the propagation medium

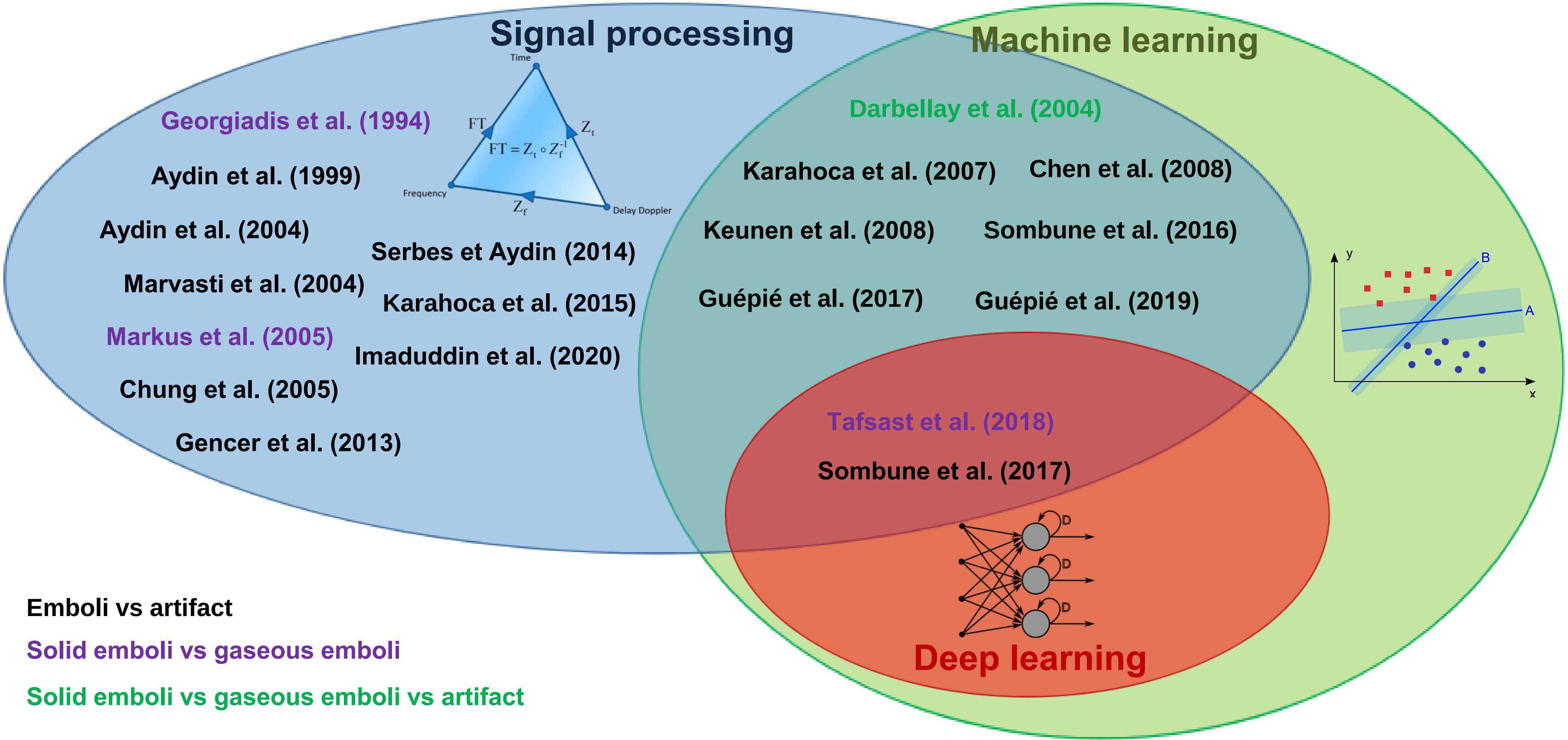
$$v_r = \frac{|f_r - f_e| \times c}{2 \times f_e \times cos(\theta)}$$

Doppler incidence angle

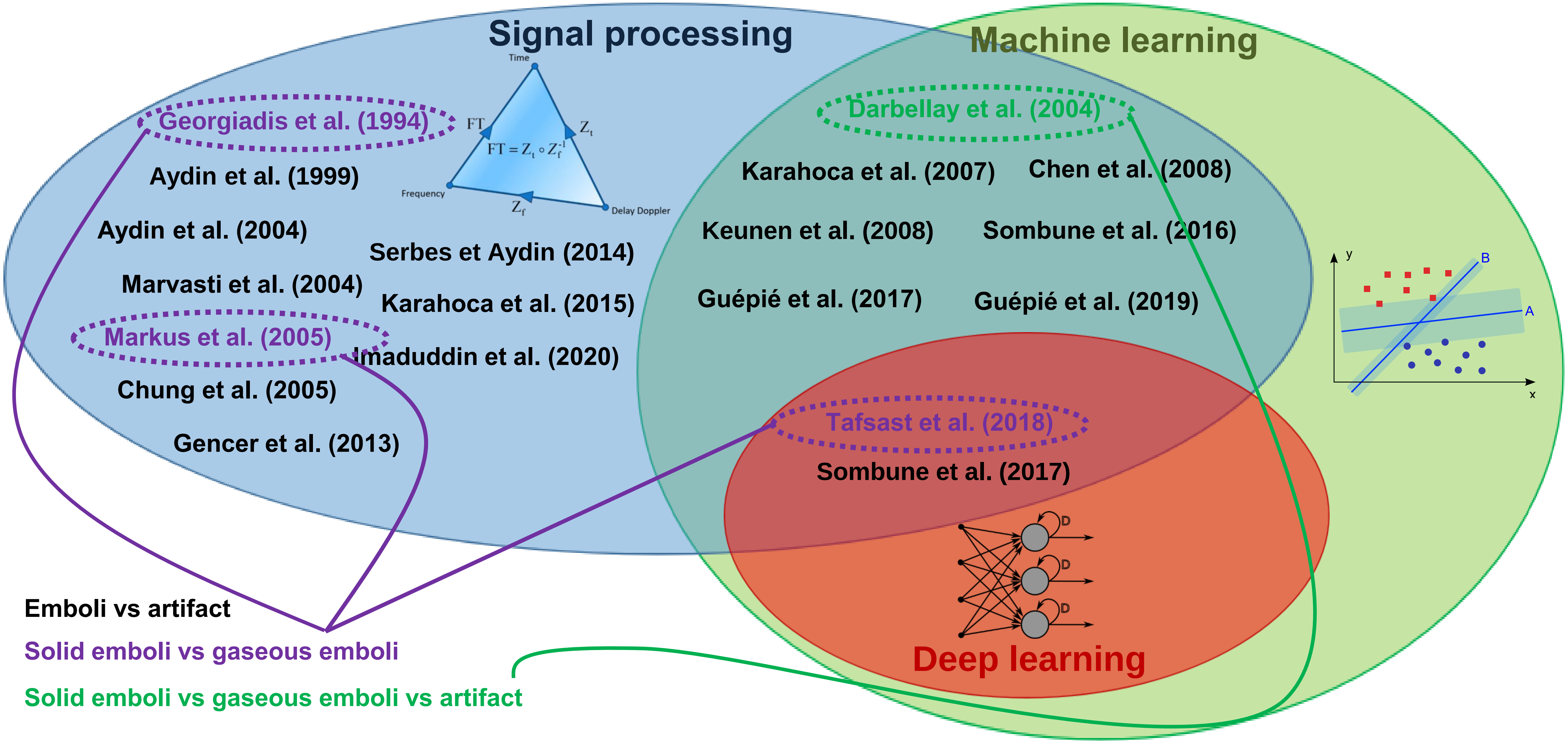
Challenges: data annotation



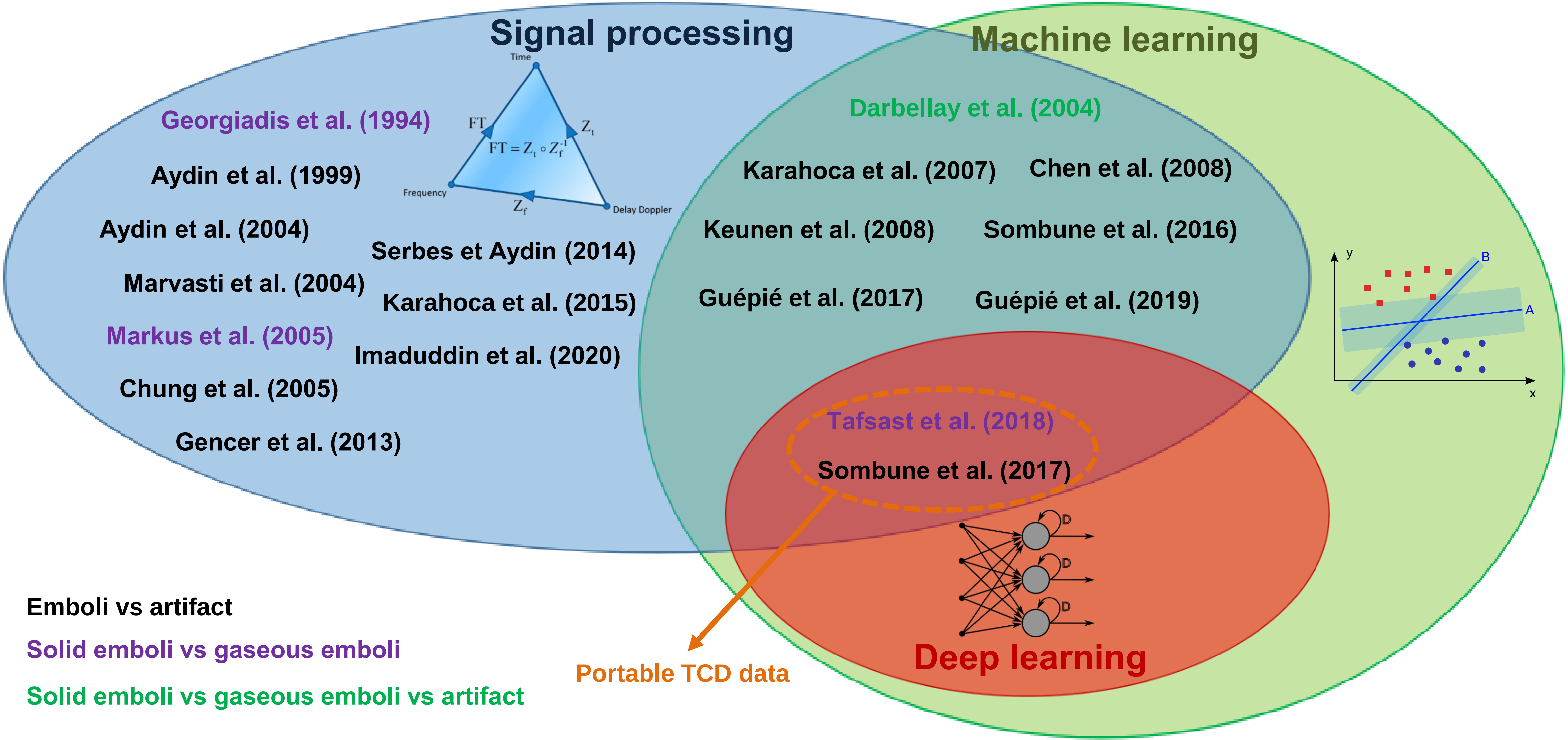
Emboli classification



Emboli classification



Emboli classification

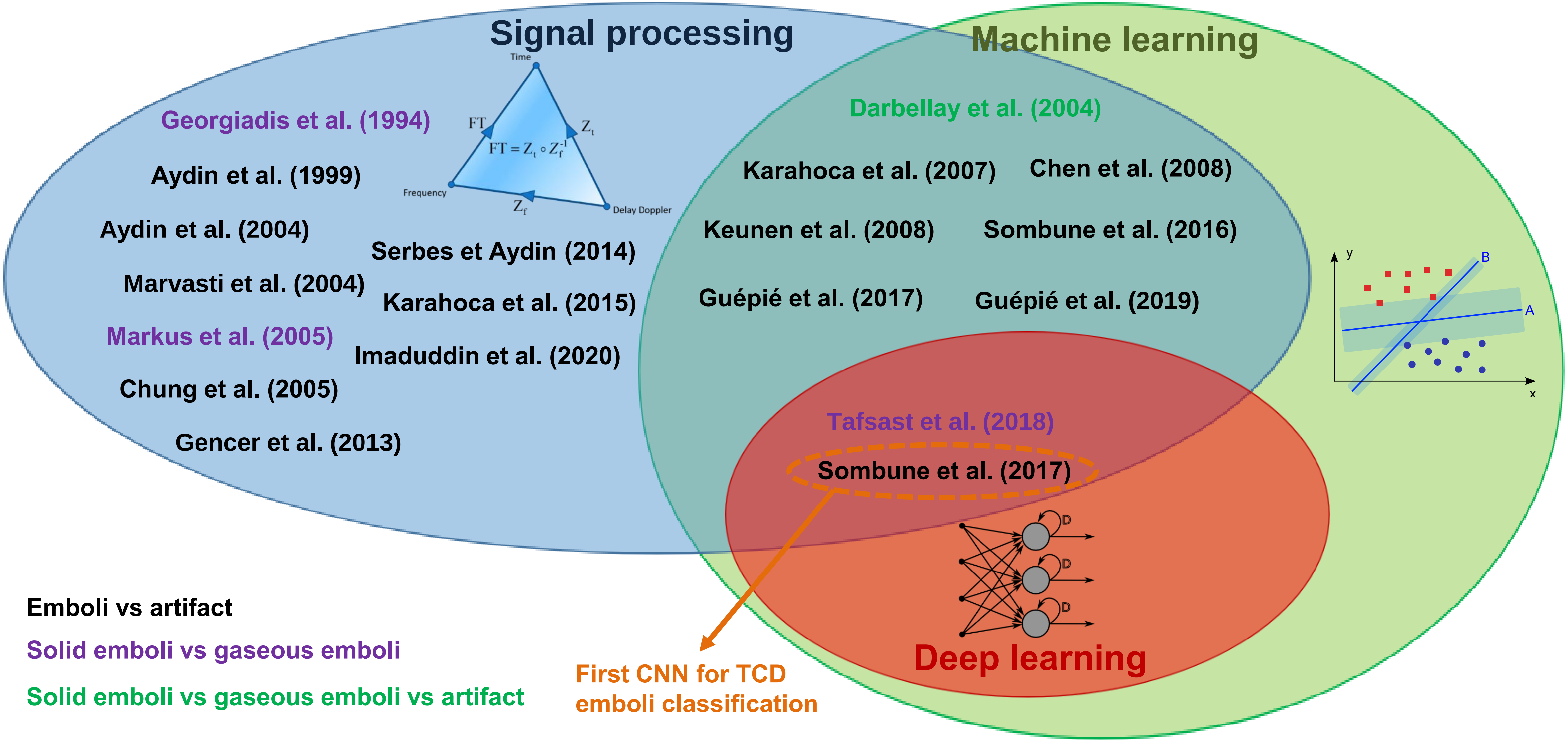


Emboli vs artifact

Solid emboli vs gaseous emboli

Solid emboli vs gaseous emboli vs artifact

Emboli classification

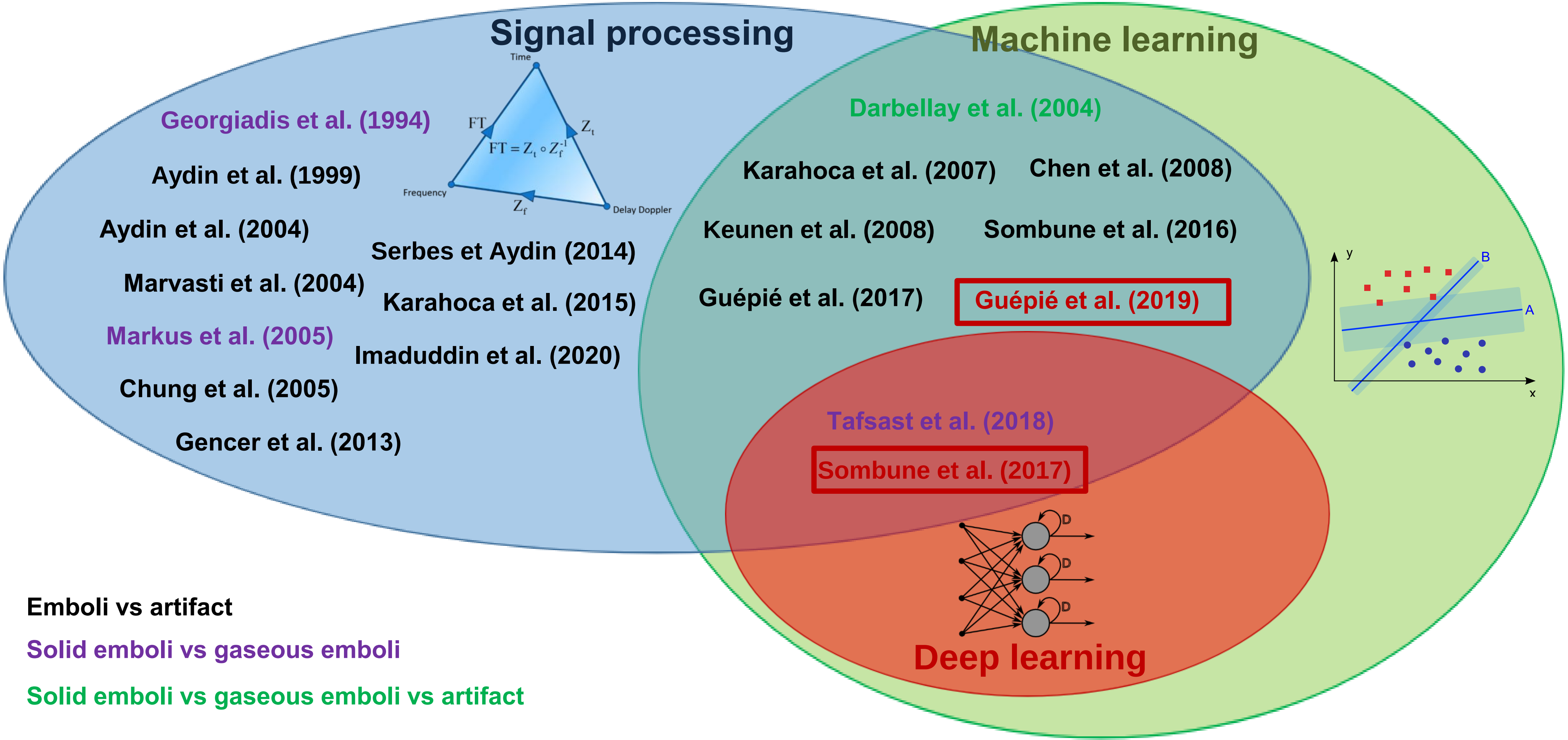


Emboli vs artifact

Solid emboli vs gaseous emboli

Solid emboli vs gaseous emboli vs artifact

Emboli classification



Emboli vs artifact

Solid emboli vs gaseous emboli

Solid emboli vs gaseous emboli vs artifact

Emboli classification

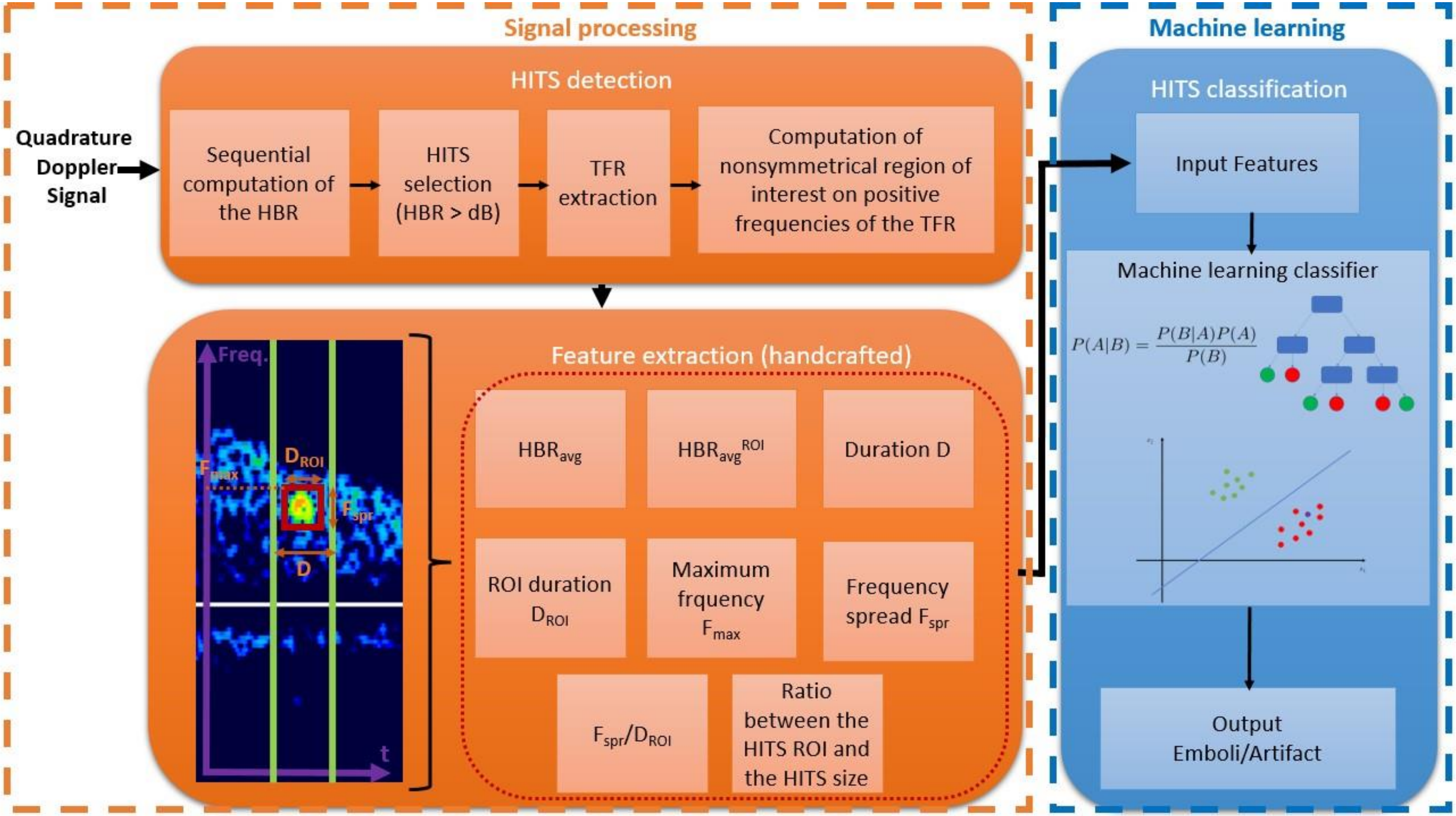


Figure – Proposed emboli detection and classification method of Guépié et al. (2019)

Emboli classification

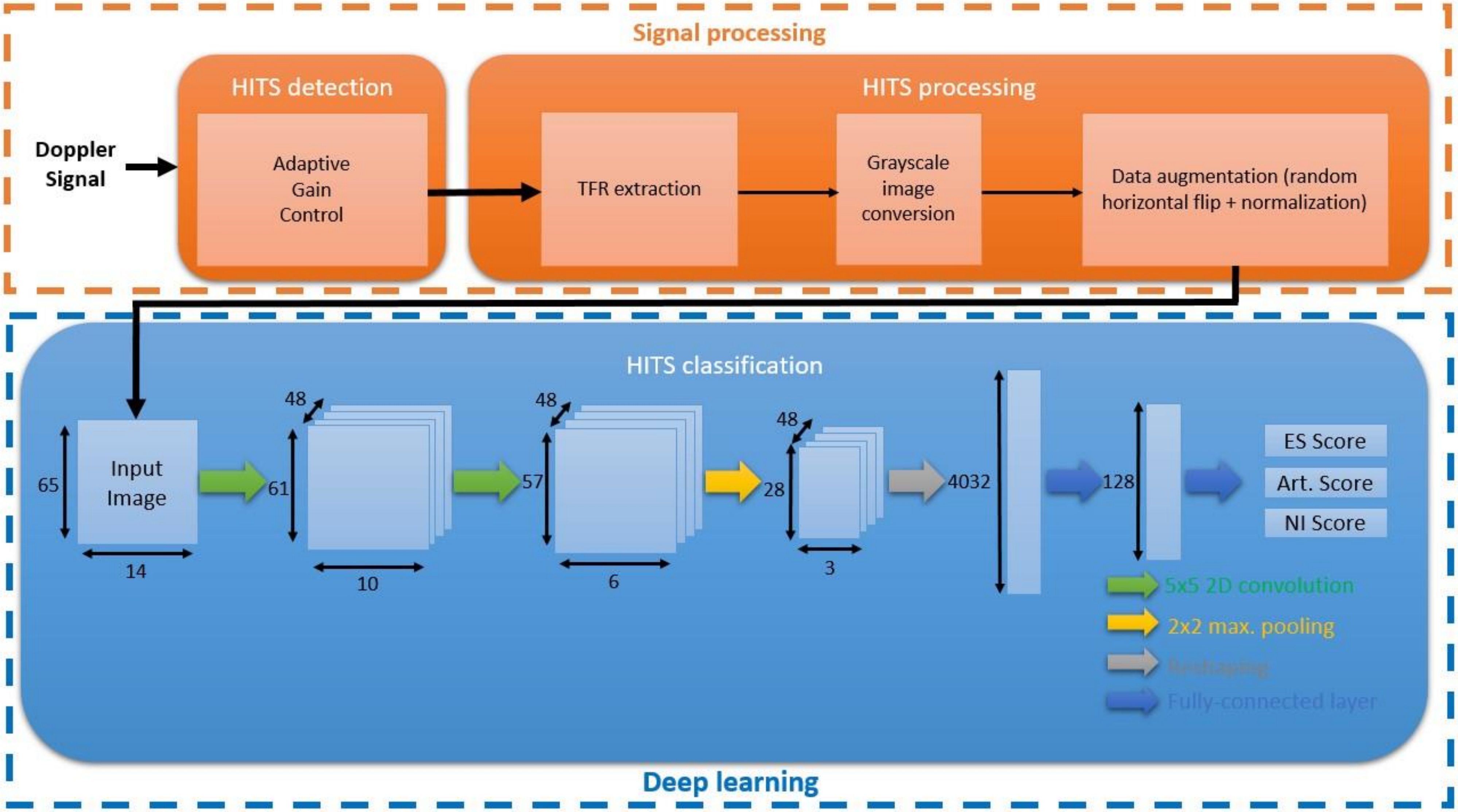
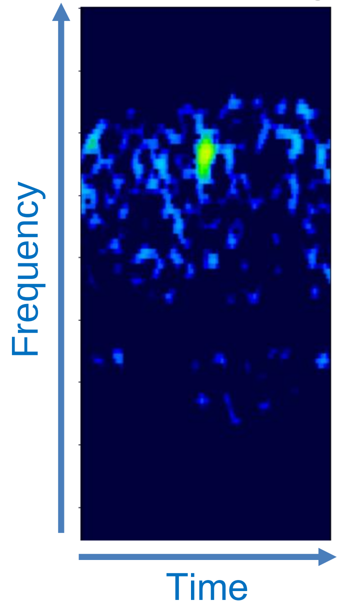


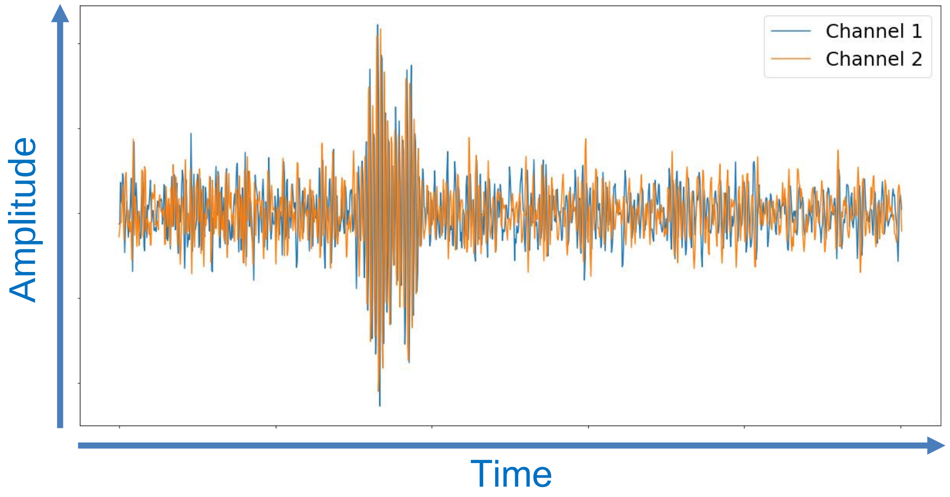
Figure – Proposed emboli HITS detection and classification by Sombune et al. (2017)

Other representations

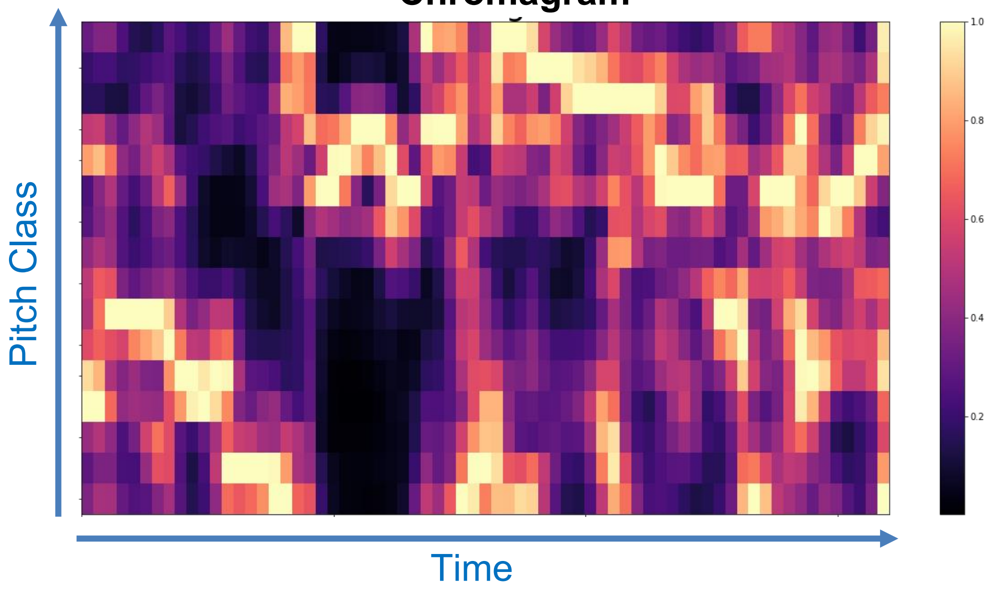
ADMS spectrogram



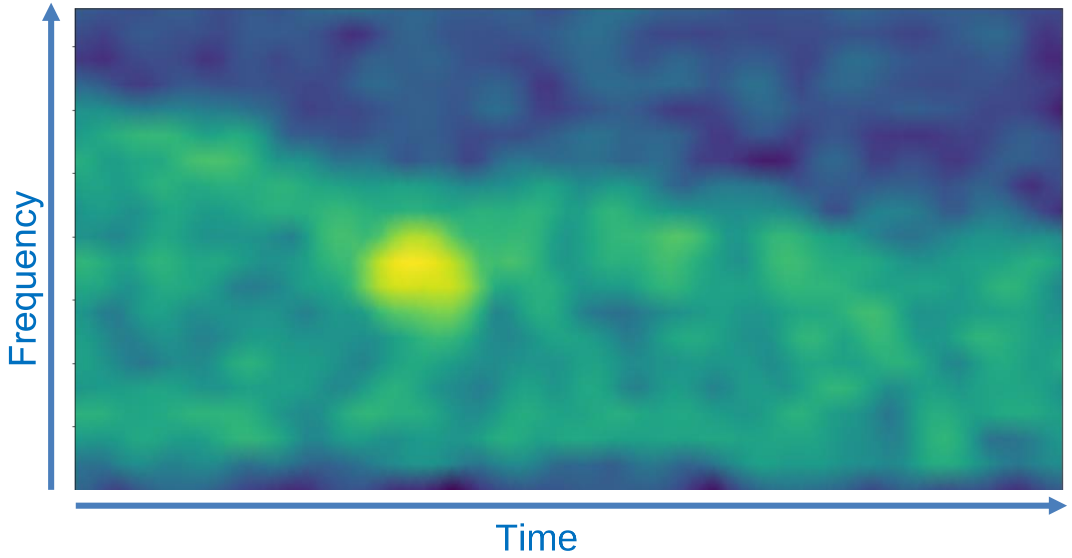
Raw Doppler Signal



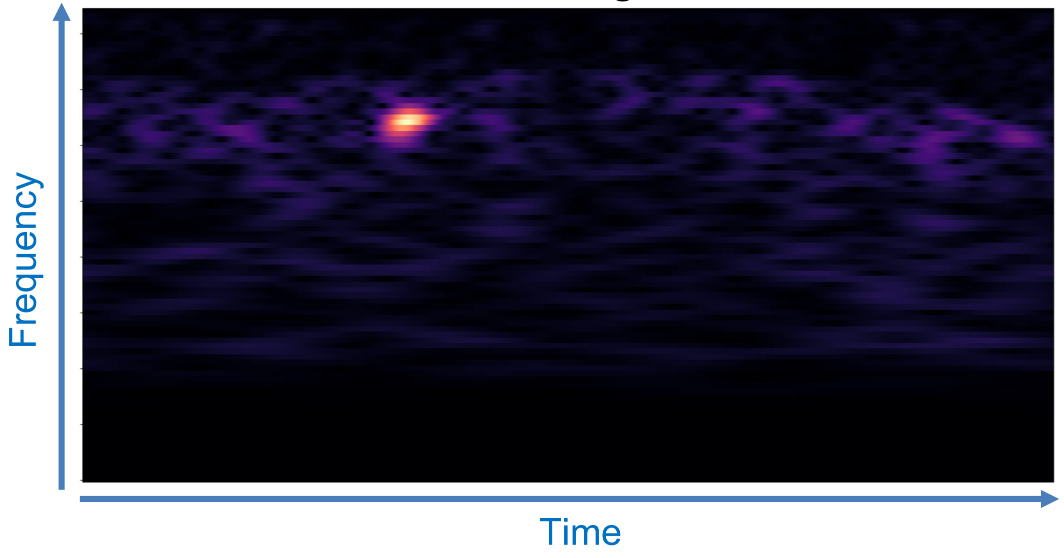
Chromagram



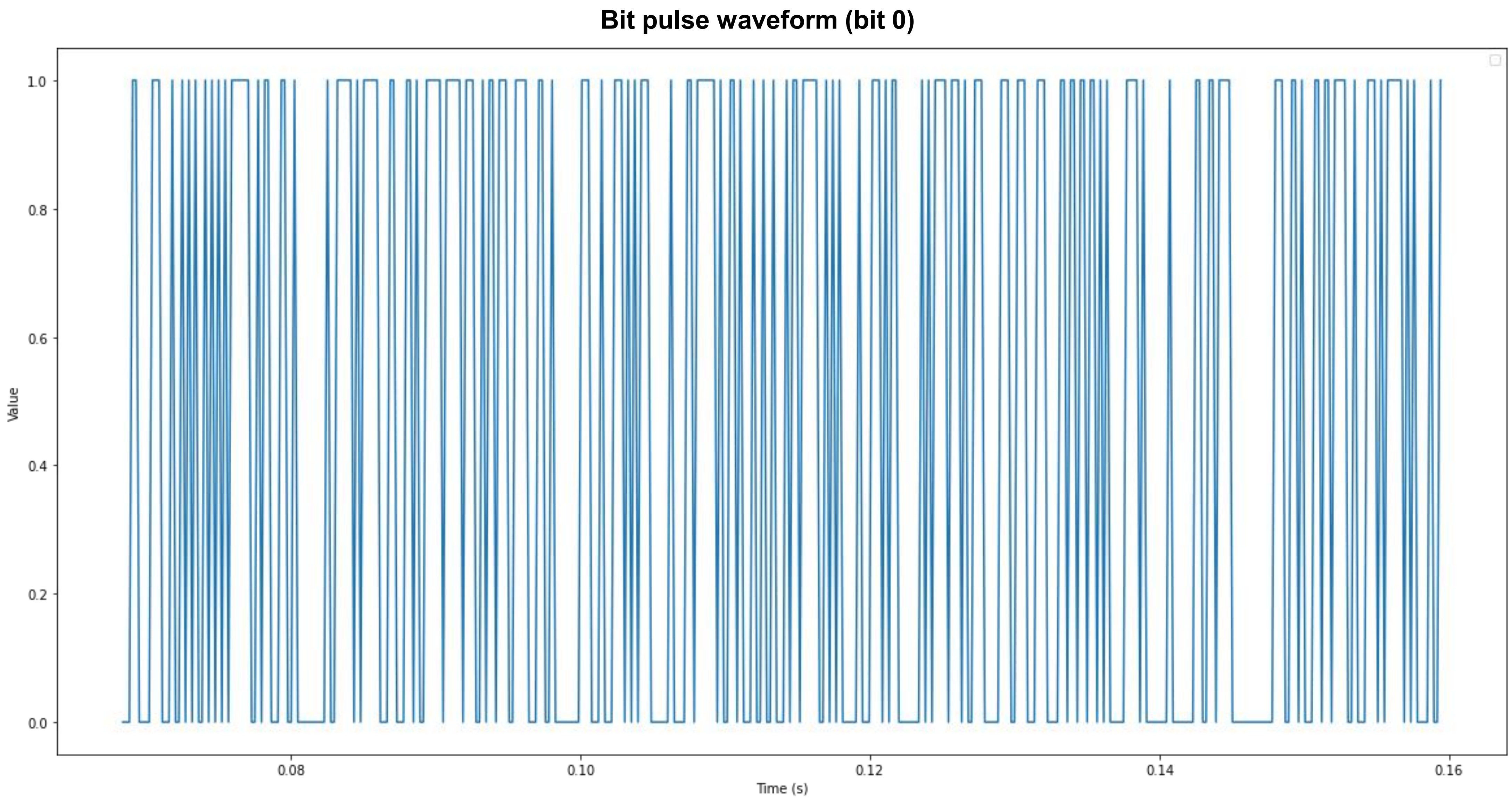
Mel spectogram



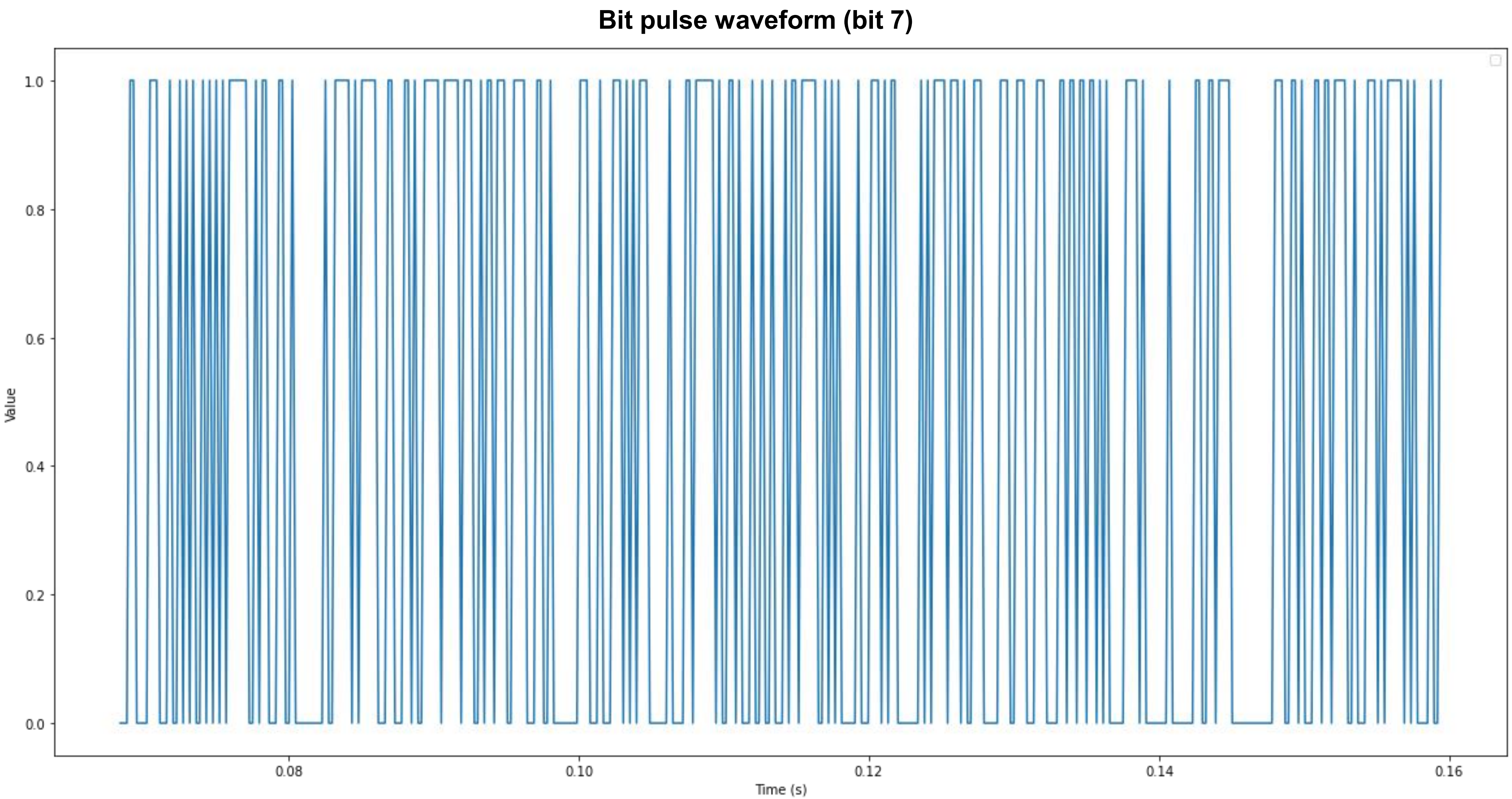
Cochleagram



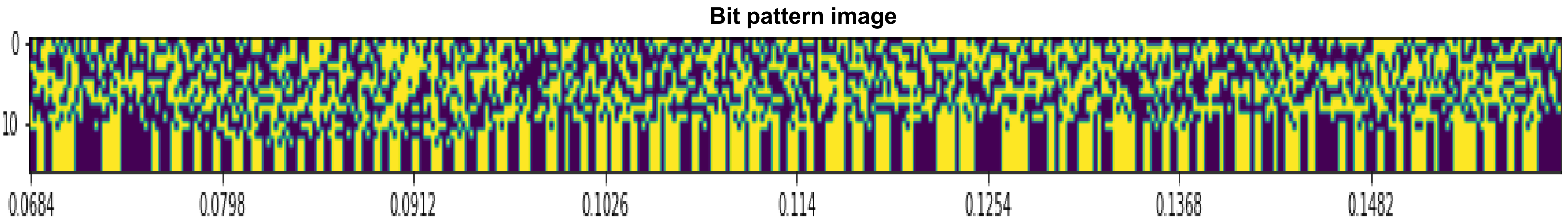
Other representations



Other representations



Other representations



Emboli classification

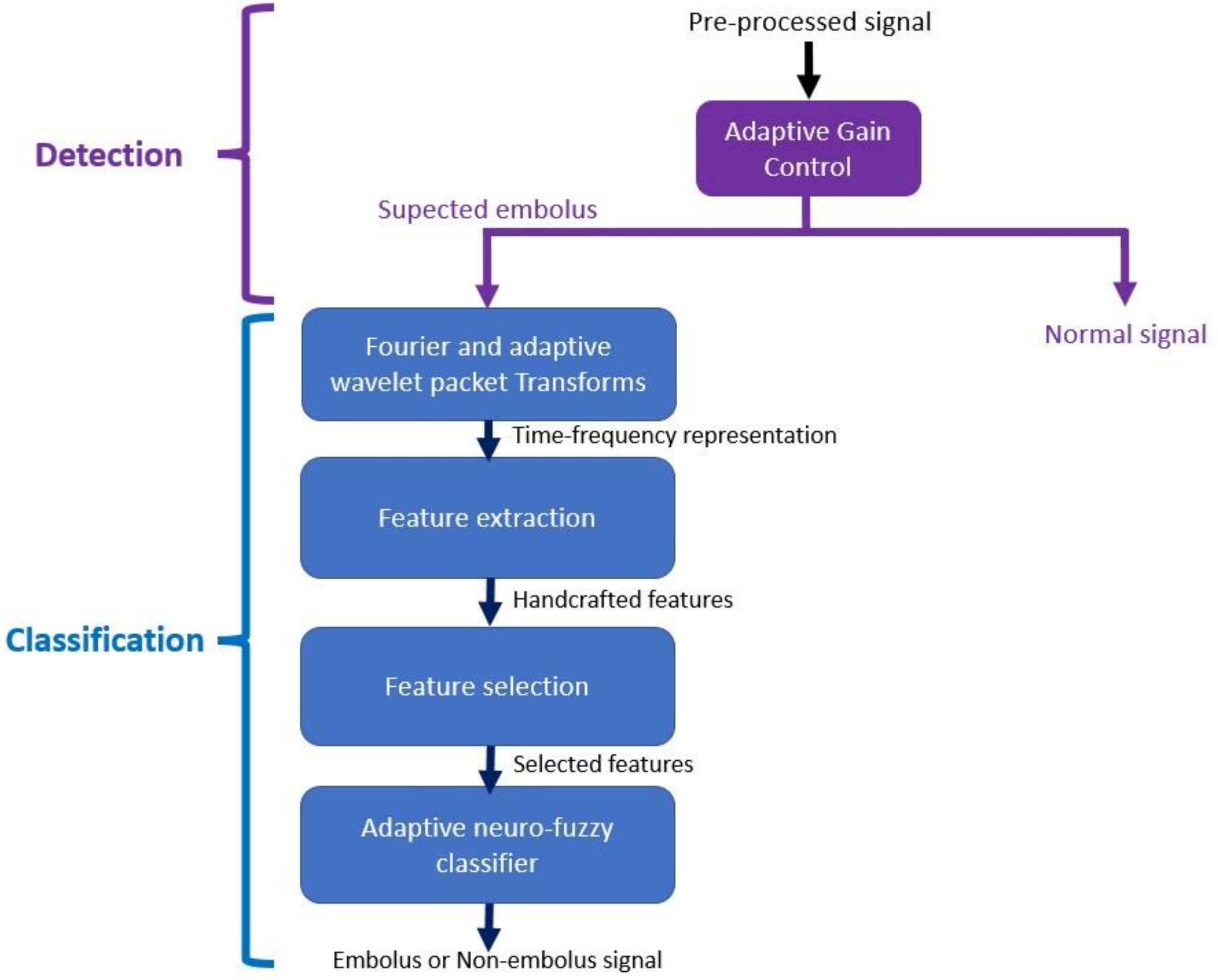


Figure – Proposed emboli ANFIS method by Sombune et al. (2016)

Emboli classification

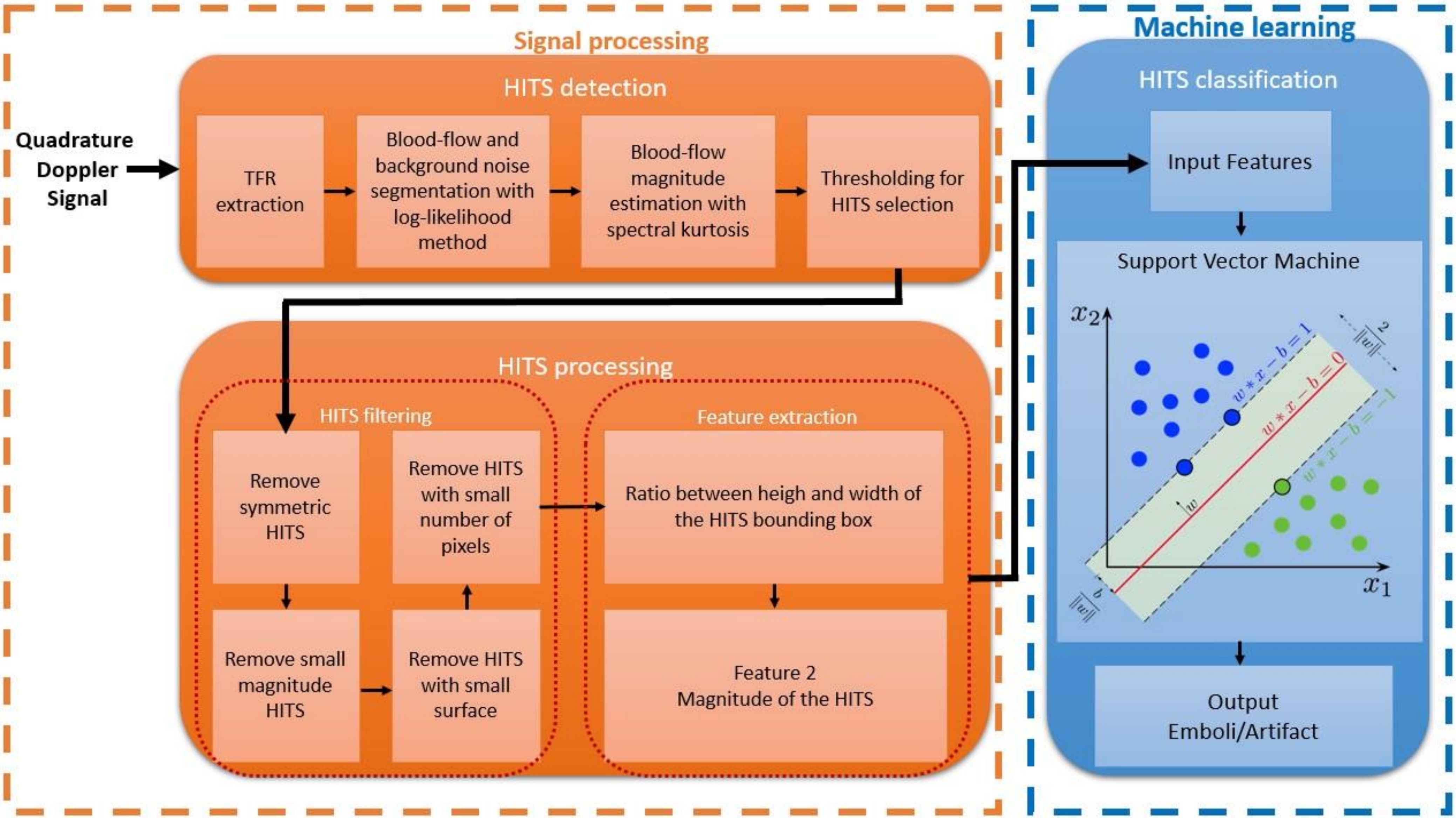


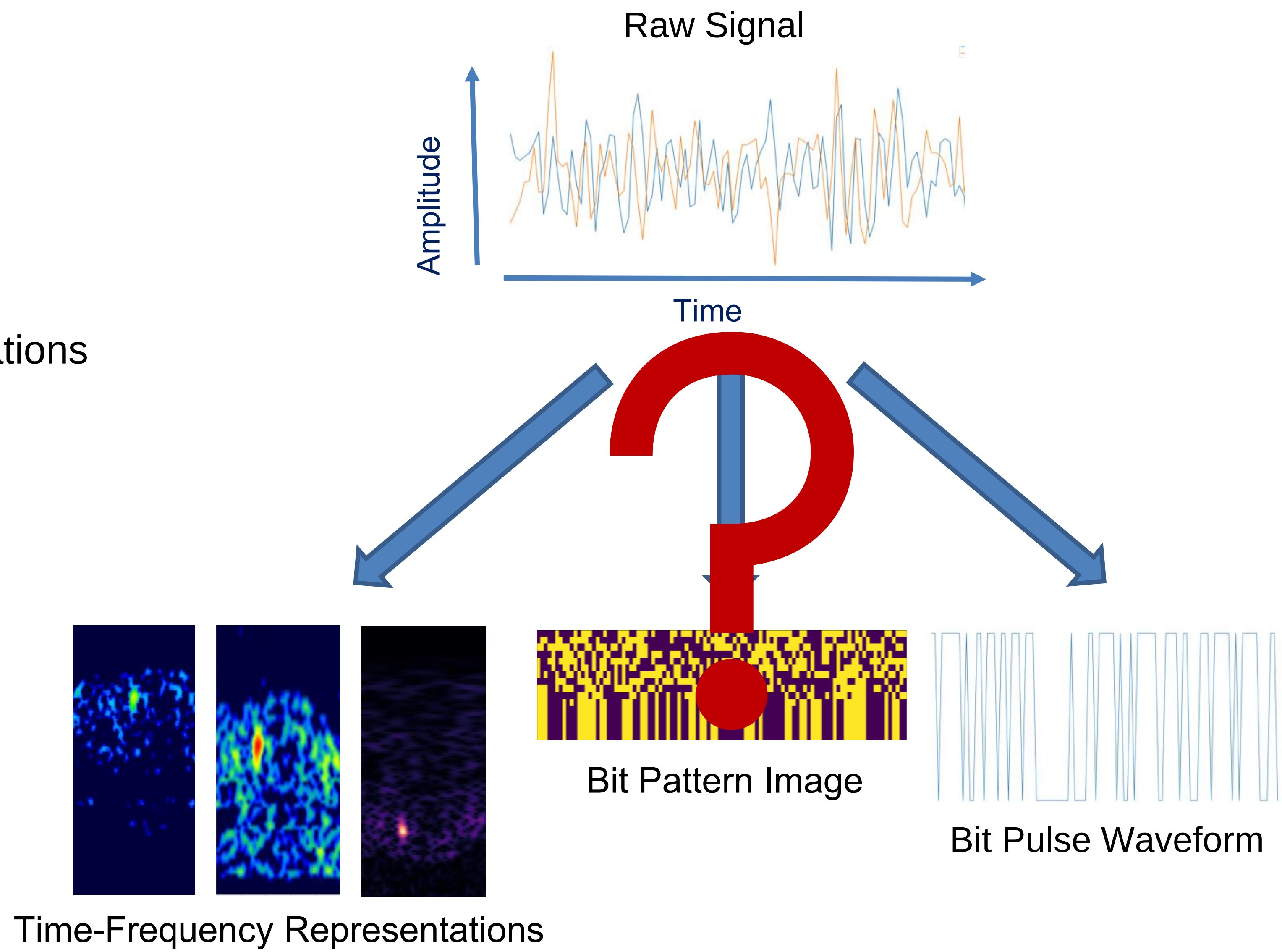
Figure – Proposed emboli detection and classification method of Guépié et al. (2017)

Emboli classification

Authors	Year	Fields	Methods	Classification	Advantages	Limitations
Markus et al.	2005	Signal Processing	-	SE vs GE	- Slightly better results than classical methods	- Use of a dual-frequency TCD - Non portable TCD
Sombune et al.	2017	Deep Learning	CNN	Artifact vs Embolus vs Normal	- No handcrafted features	- Non portable TCD - Not state-of-the-art performances
Guépié et al.	2017	Signal Processing Machine Learning	Likelihood segmentation Spectral Kurtosis, SVM	Artifact vs Embolus	- Good classification performance - Adapt to patients - Operator independent - Portable TCD	- Handcrafted features - No distinction between emboli
Tafsast et al.	2018	Deep Learning	CNN	SE vs GE	Good classification results	- In-vitro study
Guépié et al.	2019	Signal Processing Machine Learning	SVM, Naive Bayes, Decision Tree	Artifact vs Embolus	- State-of-the-art results - Adapt to patients - Operator independent - Sequential Method - Portable TCD	- Handcrafted features - No distinction between emboli

Challenges: optimal representation

- Temporal dependence.
- One modality, different representations
- Optimal representation ?
- Feature combination ?



Challenges: model compression

Limited memory resources.

Limited computation resources.

Energy constraints.

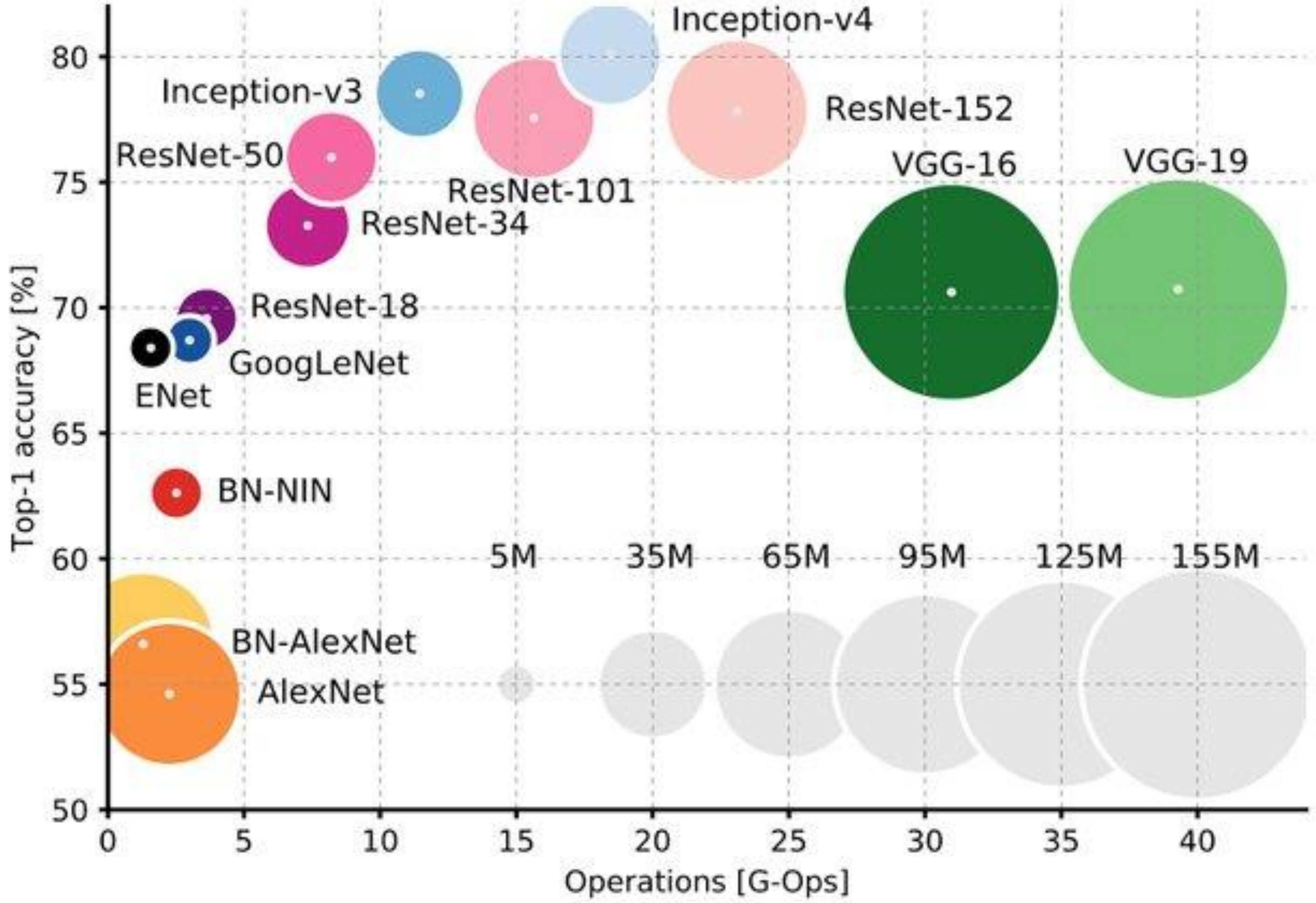


Figure – Classification accuracy based on the size and number of floating-point operations of different deep learning models (Abbas et al. 2021)

Challenges: limited resources

- Limited memory.
- Inference time.

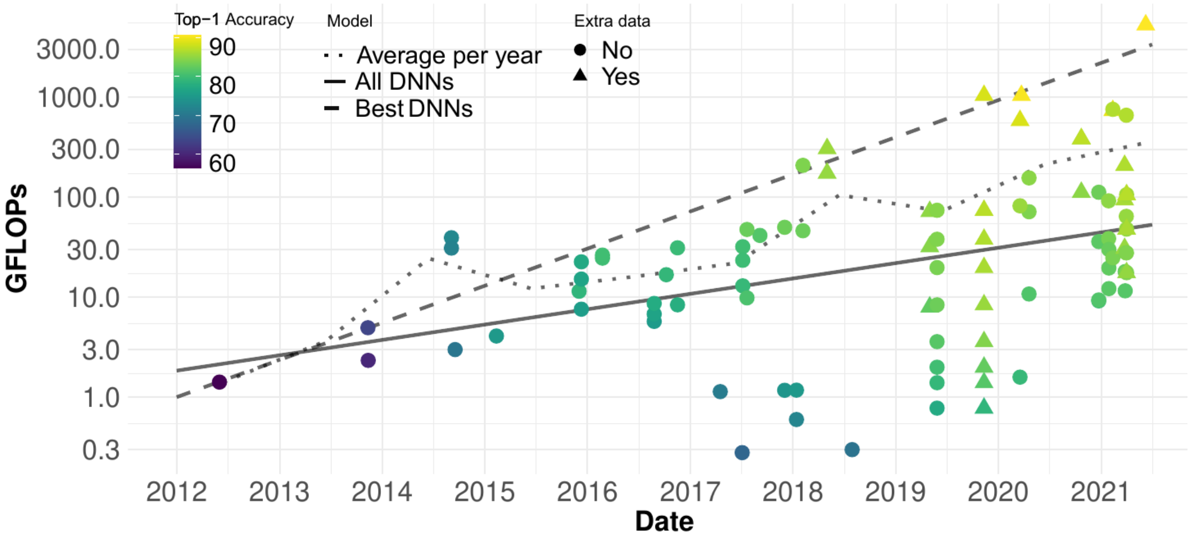


Figure – GFLOPs over the years. The dashed line is a linear fit (logarithmic y-axis) for the models with highest accuracy per year. Desislavov et Martinez-Plumed (2021).

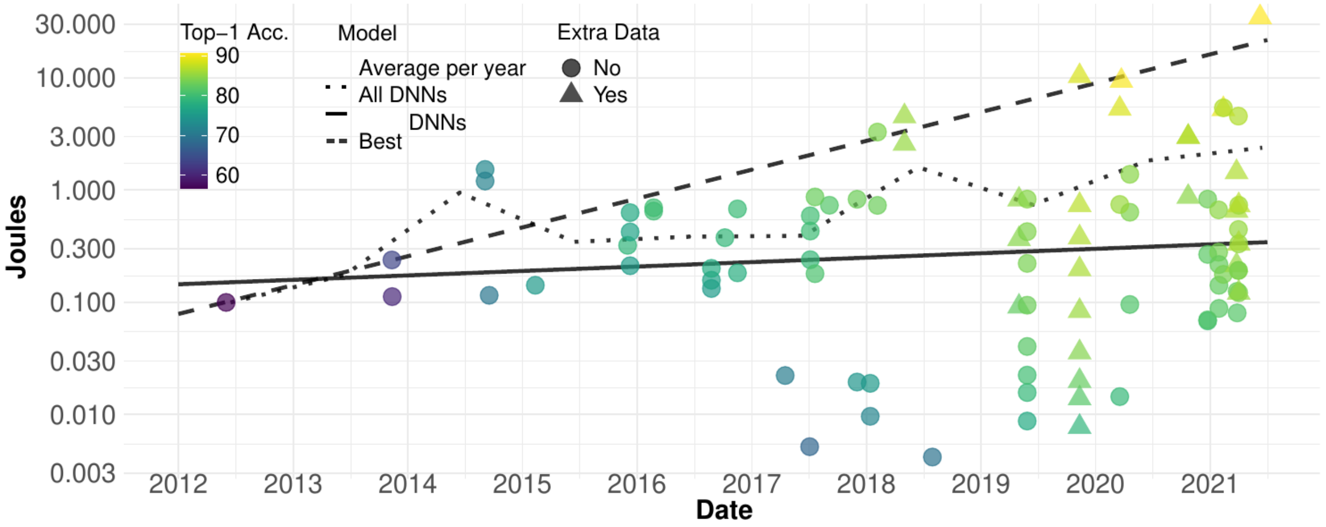
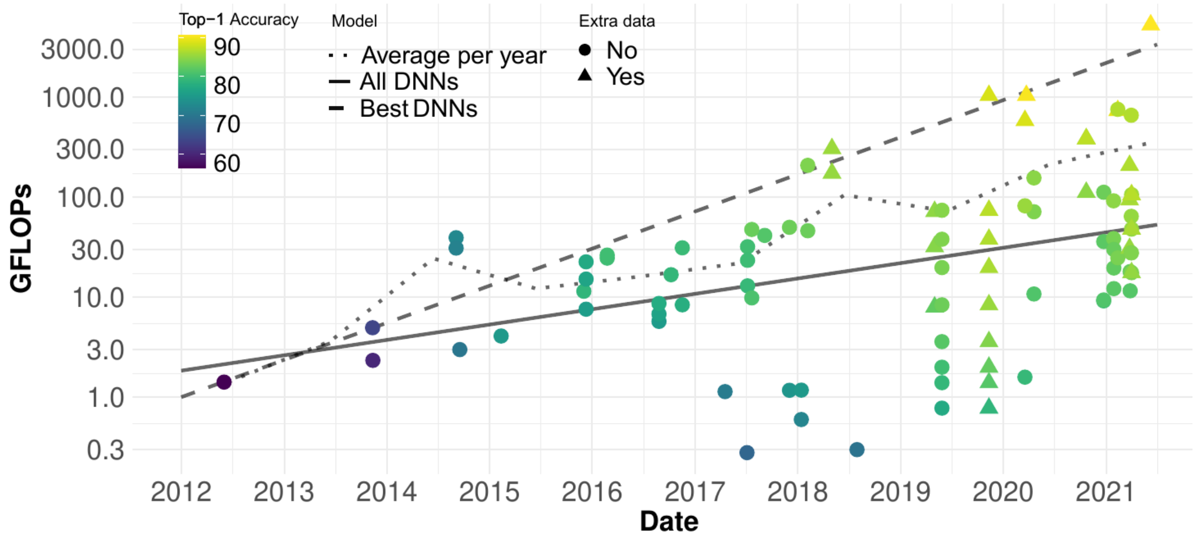


Figure – Estimated Joules of a forward pass (CV). The dashed line is a linear fit (logarithmic y-axis) for the models with highest accuracy per year. Desislavov et Martinez-Plumed (2021).

Challenges: limited resources

- Limited memory.
- Inference time.
- Energy consumption.



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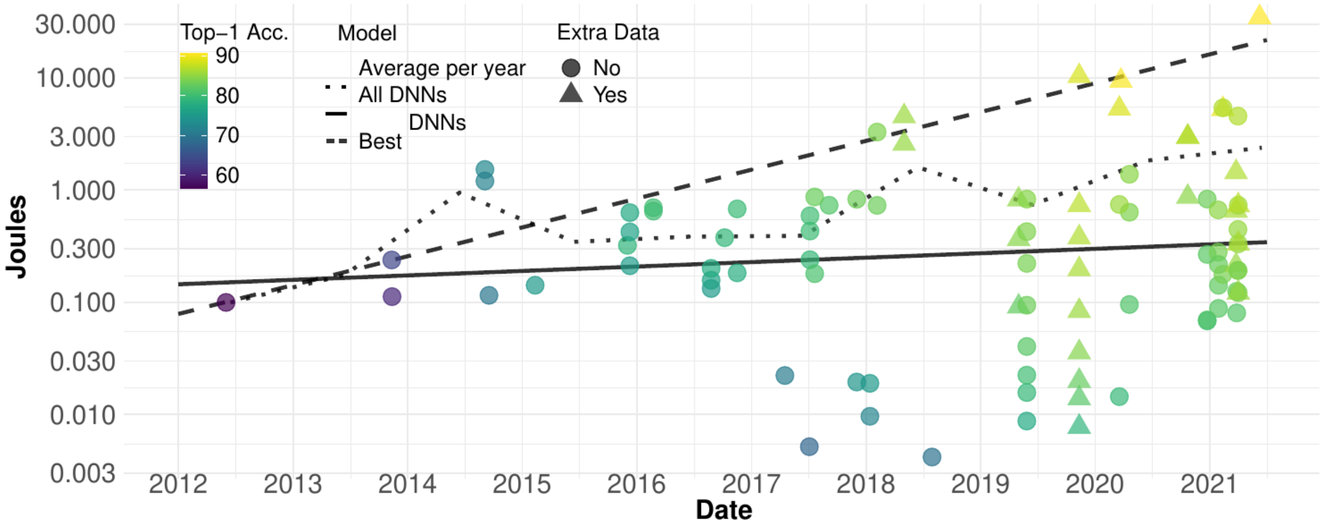


Figure – Estimated Joules of a forward pass (CV). The dashed line is a linear fit (logarithmic y-axis) for the models with highest accuracy per year. Desislavov et Martinez-Plumed (2021).

Contribution 1 : Semi-automatic data annotation

Possible solution to noisy-labels

Category		P1 Flexibility	P2 No Pre-train	P3 Full Exploration	P4 No Supervision	P5 Heavy Noise	P6 Complex Noise
Robust Loss Function		○	○	○	○	×	×
Robust Architecture	Noise Adaptation Layer	△	○	○	○	×	×
	Dedicated Architecture	×	○	○	×	△	○
Robust Regularization		○	○	○	○	△	△
Loss Adjustment	Loss Correction	○	○	○	×	×	×
	Loss Reweighting	○	○	○	○	×	△
	Label Refurbishment	○	○	○	△	×	△
Sample Selection		○	○	×	×	○	△
Meta Learning	Fast Adaptation	○	○	○	△	△	○
	Learning to Update	○	○	○	×	△	○
Semi-supervised Learning		○	△	○	○	○	△

Figure – Table from Song et al. 2020. *O* means completely supported, △ means partially supported and × means not supported.

Input sample # classes

Model One-hot label k^{th} element

$$\mathcal{L}_{GCE}(f(X), \bar{y}) = \sum_{k=1}^{K} \frac{\bar{y}_k - f_k(X)^q}{q}$$

$q \rightarrow 0$: $\mathcal{L}_{CE}(f(X), \bar{y})$ **Noise sensitive**

$q \rightarrow 1$: $\mathcal{L}_{MAE}(f(X), \bar{y})$ **Noise tolerant**

Noisy-labels

Category		Method	P1	P2	P3	P4	P5	P6
Robust Loss Function		*Robust MAE*	O	O	O	O	×	×
		Generalized Cross Entropy	O	O	O	O	×	×
		Symmetric Cross Entropy	O	O	O	O	×	×
		Curriculum Learning	O	O	O	×	O	△
Robust Architecture	Noisy Adaptation Layer	*Webly Learning*	△	×	O	O	×	×
		Noise Model	△	O	O	O	×	×
		Dropout Noise Model	△	O	O	O	×	×
		S-model	△	O	O	O	×	×
		C-model	△	O	O	O	×	O
		NLNN	△	O	O	O	×	×
	Dedicated Architecture	*Probablistic Noise Model*	×	×	O	×	△	O
		Masking	×	O	O	×	△	O
		Contrastive-Additive Noise Network	×	O	O	O	△	O
Robust Regularization		*Adversarial Training*	O	O	O	O	△	△
		Label Smoothing	O	O	O	O	△	△
		Mixup	O	O	O	O	△	△
		Bilevel Learning	O	O	O	×	△	△
		Annotator Confusion	O	×	O	O	△	△
		Pre-training	O	×	O	O	△	△
Loss Adjustment	Loss Correction	*Backward Correction*	O	O	O	×	×	×
		Forward Correction	O	O	O	×	×	×
		Gold Loss Correction	O	×	O	×	×	×
	Loss Reweigting	*Importance Reweighting*	O	O	O	O	×	△
		Active Bias	O	O	O	O	×	△
	Label Refurbishment	*Bootstrapping*	O	O	O	×	×	△
		Dynamic Bootstrapping	O	O	O	O	×	△
		D2L	O	O	O	O	×	△
		SELFIE	O	O	O	×	O	△

Category		Method	P1	P2	P3	P4	P5	P6
Sample Selection		*Decouple*	O	O	×	O	×	△
		MentorNet	×	×	×	×	O	△
		Co-teaching	O	O	×	×	O	△
		Co-teaching+	O	O	×	×	O	△
		Iterative Detection	O	O	×	O	O	△
		ITLM	O	O	×	×	O	△
		INCV	O	O	×	O	O	△
Meta Learning	Fast Adaption	*Meta-Regressor*	O	O	O	×	O	O
		MLNT	O	O	O	O	×	O
	Learning to Update	*Knowledge Distillation*	O	×	O	×	△	O
		L2LWS	×	O	O	×	△	O
		CWS	×	O	O	×	△	O
		Automatic Reweighting	O	O	O	×	△	O
		Meta-Weight-Net	△	O	O	×	△	O
		Data Coefficients	O	O	O	×	O	O
Semi-supervised Learning		*Label Aggregation*	O	×	O	×	×	△
		Two-Stage Framework	O	×	O	O	O	△
		SELF	O	O	O	O	O	△
		DivideMix	O	O	O	O	O	△

Figure – Table from Song et al. 2020. *O* means completely supported, △ means partially supported and × means not supported.

OPF-semi

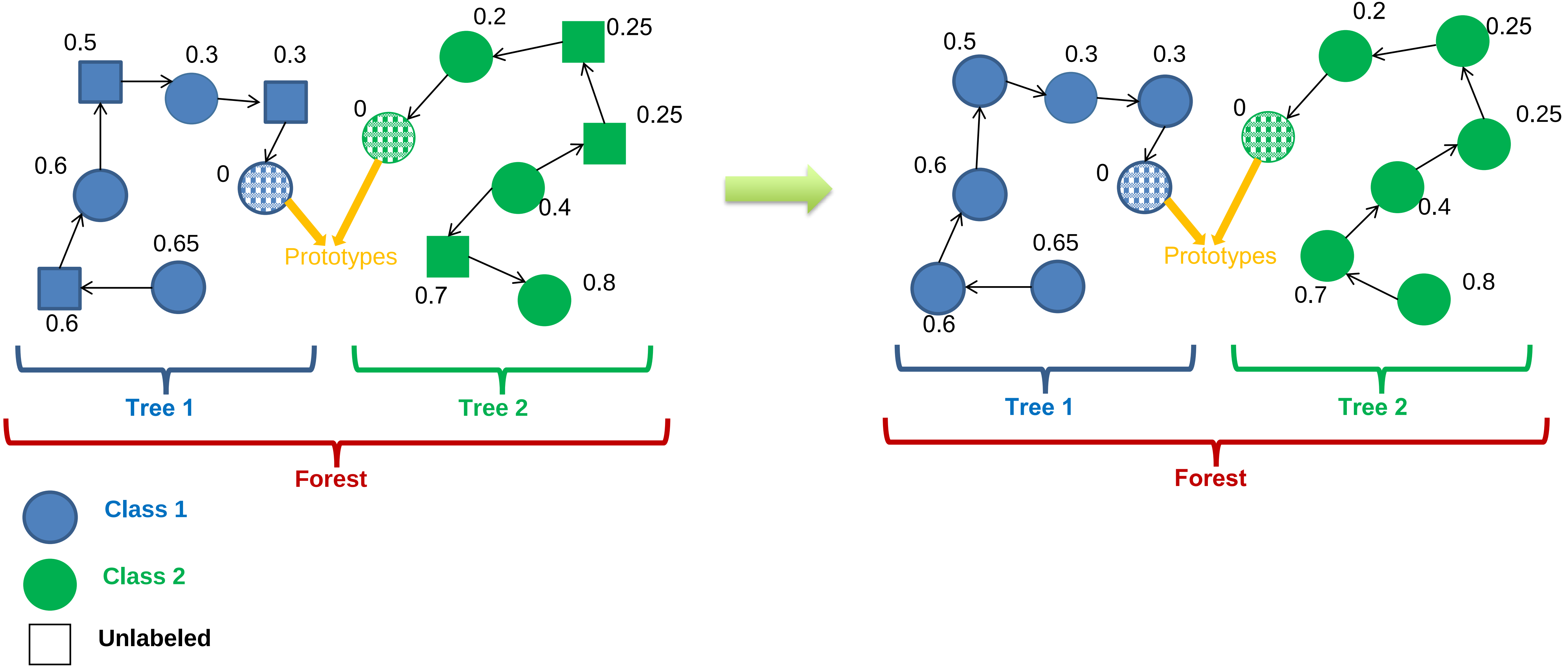


Figure – Semi-supervised optimum path forest (OPF-semi) (**Amorim et al., 2014**)

Co-ranking framework: local quality

$$Q_L^i(k_s,k_t) = \frac{1}{2\times k_s \times N}\times\sum_{j=1}^{N}(\underline{\mu_t(R_{ij},r_{ij},k_t)}\times\underline{\mu_s(R_{ij},r_{ij},k_s)}+\underline{\mu_t(R_{ji},r_{ji},k_t)}\times\underline{\mu_s(R_{ji},r_{ji},k_s)})$$

Size of the neighborhood to consider

Rank significance

$$\boxed{\mu_s(R_{ij},r_{ij},k_s)} = \begin{cases} 1 \text{ if } R_{ij} \le k_s \text{ or } r_{ij} \le k_s \\ 0 \text{ else} \end{cases}$$

Rank error tolerance

$$\boxed{\mu_t(R_{ij},r_{ij},k_t)} = \begin{cases} 1 \text{ if } |R_{ij} - r_{ij}| \le k_t \\ 0 \text{ else} \end{cases}$$

Size of the tolerated ranks errors

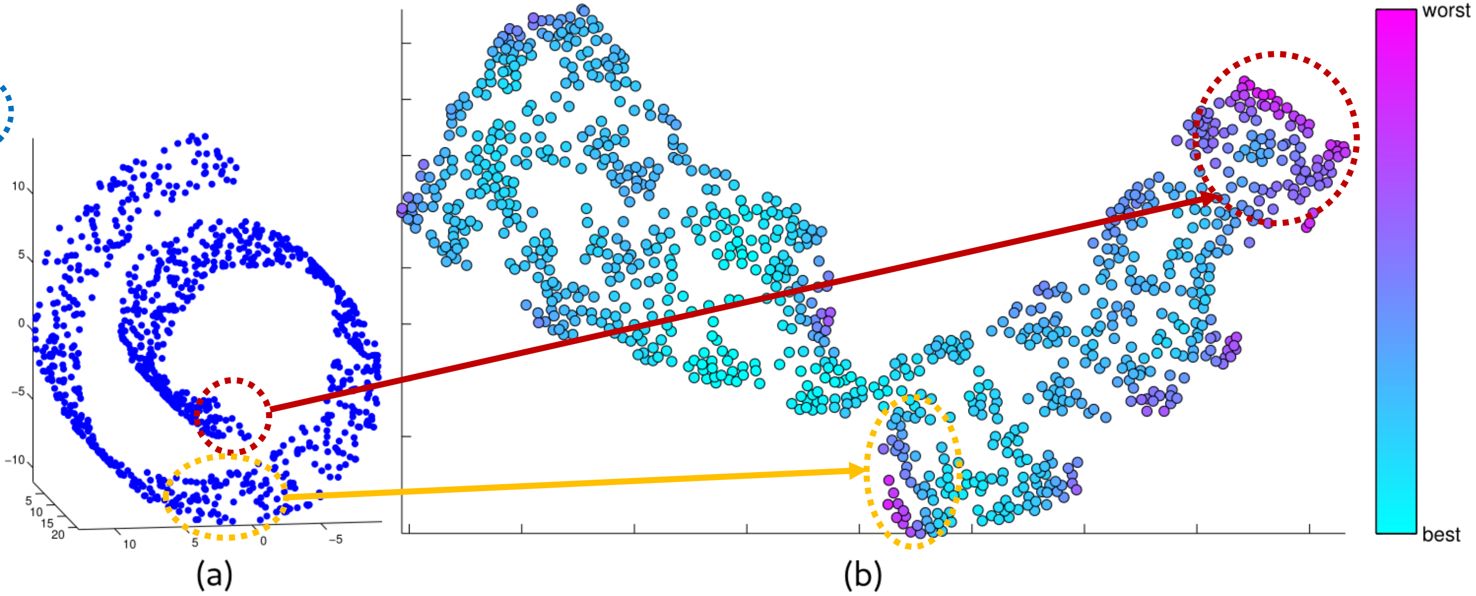


Figure – Illustration of the local quality metric on the Swiss roll benchmark dataset (**Lueks et al., 2011**).

Global pipeline

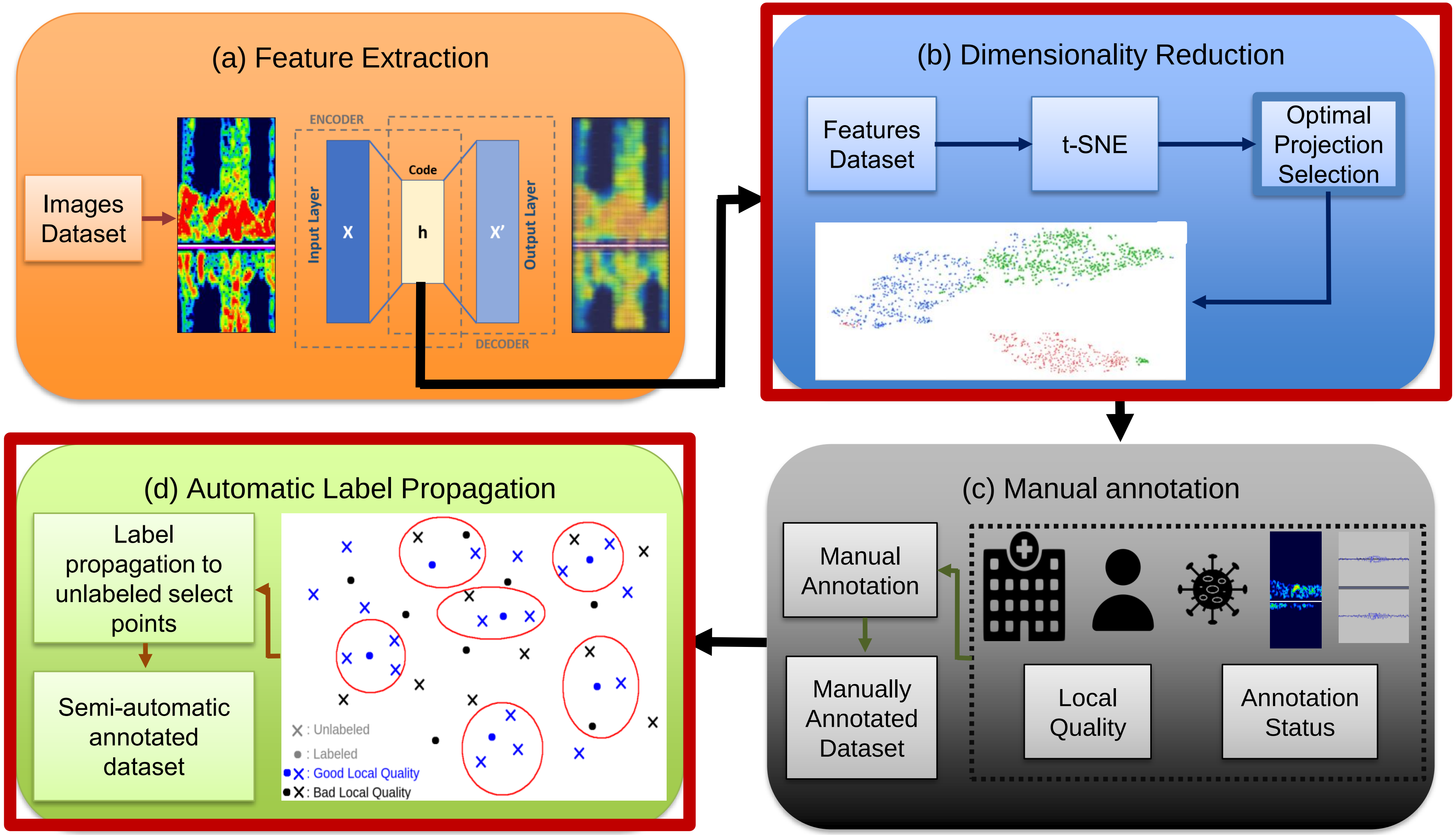


Figure – Global pipeline of our proposed semi-automatic data annotation approach.

Proposed pipeline

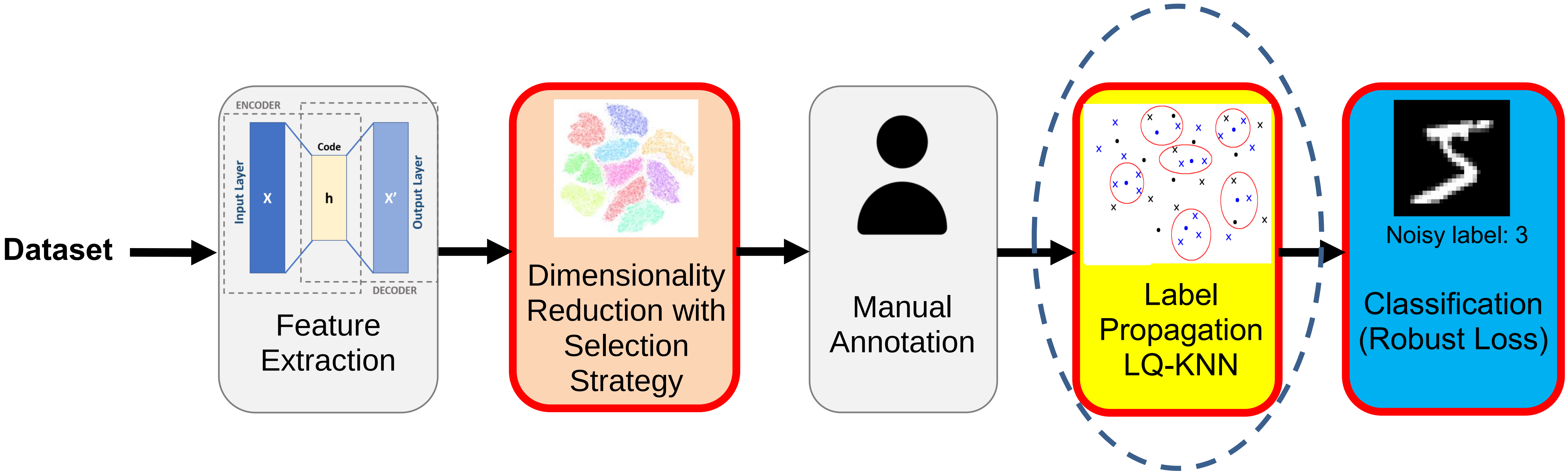
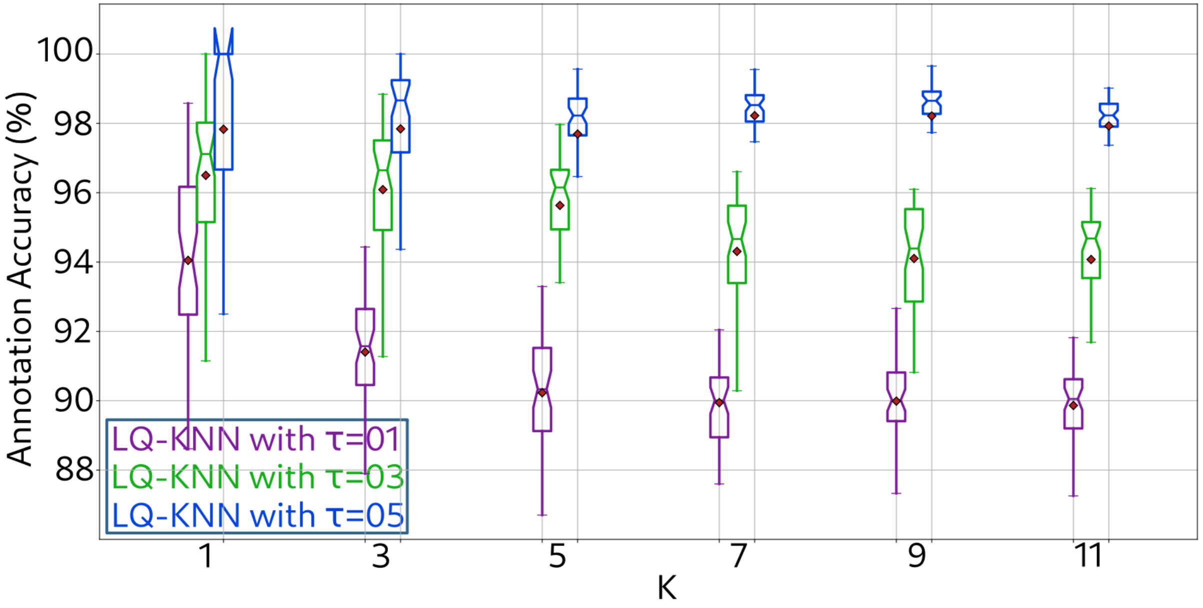


FIGURE - Semi-Automatic Data Annotation Method

Contribution 1.a.: Semi-automatic data annotation method **state-of-the-art comparison**



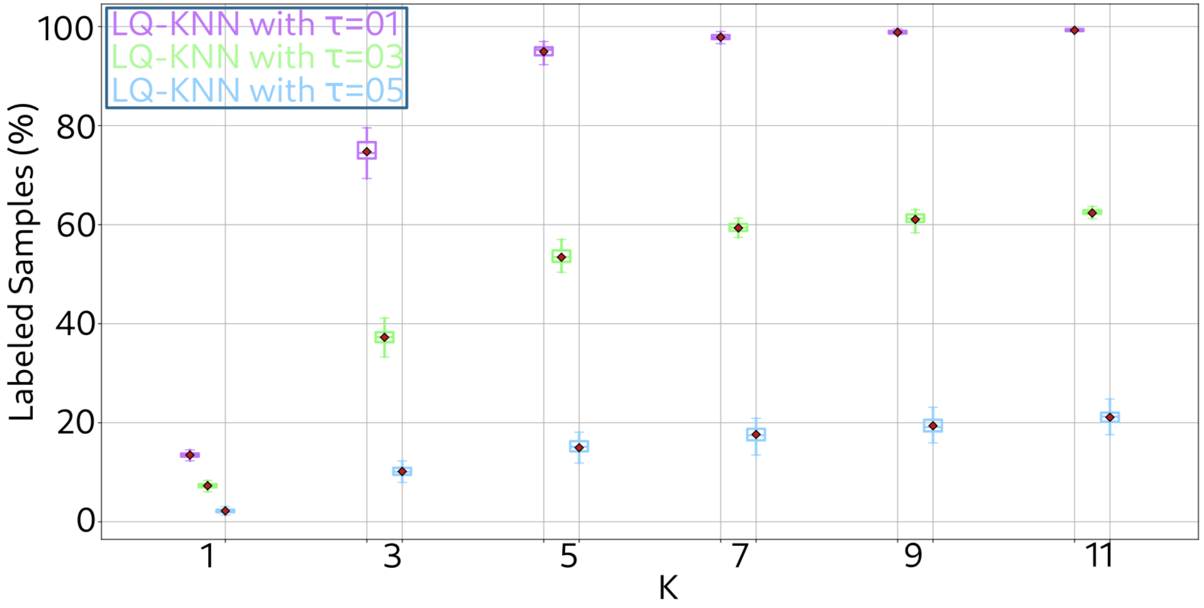


Figure - Comparison of *LQ-KNN* label propagation with different hyper-parameters using a HITS dataset

Proposed pipeline

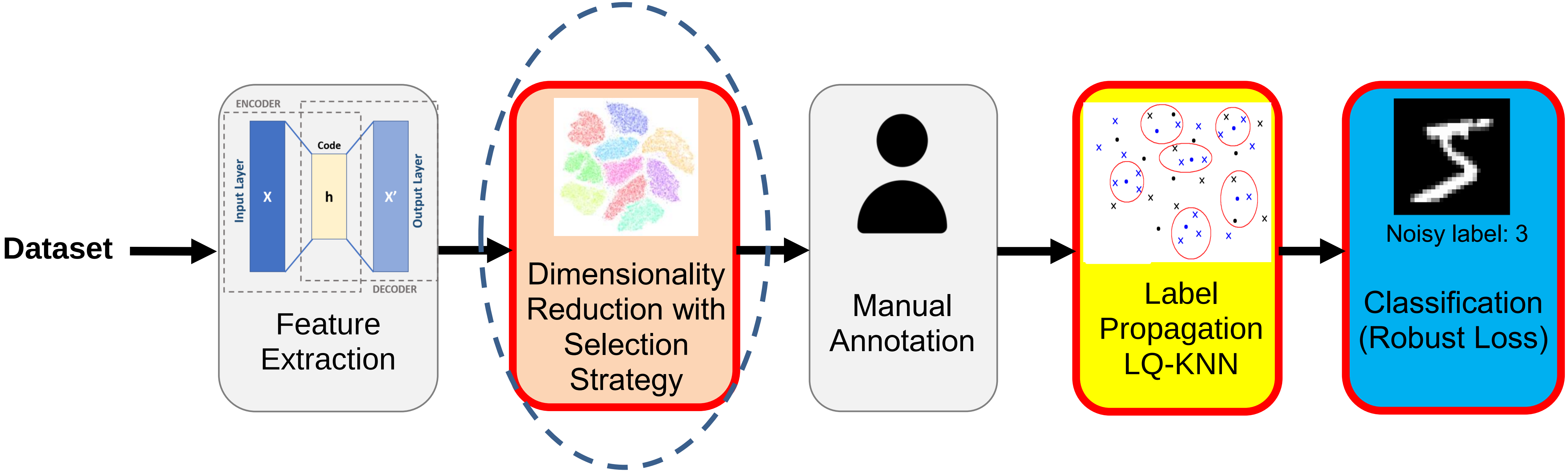


FIGURE - Semi-Automatic Data Annotation Method

Dimensionality Reduction

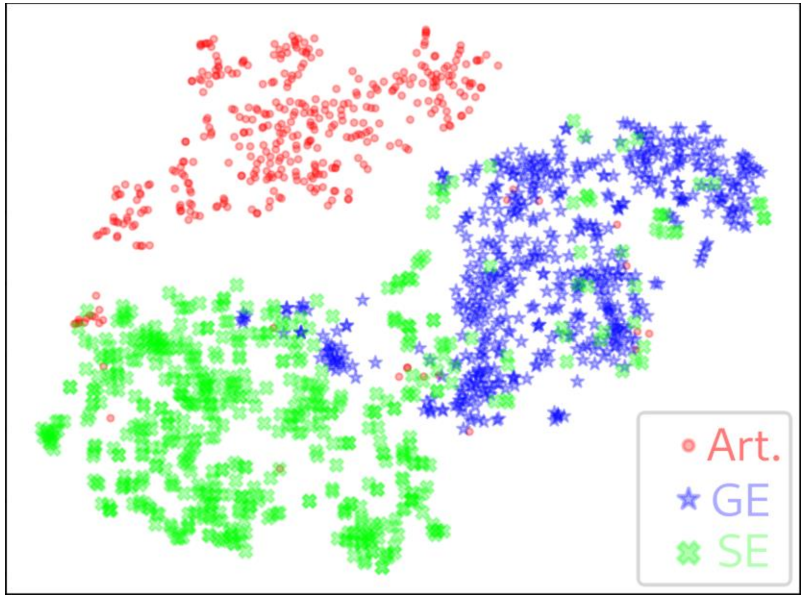
Silhouette Score[1]

Compares the **similarity** of a sample k **between** :
- The **samples** of its **own class**.
- The samples of **other classes**.

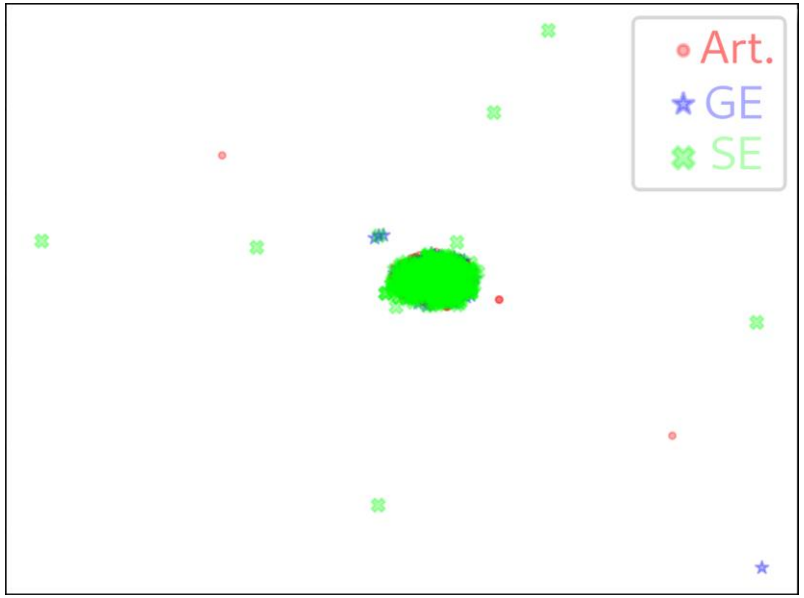
==> The higher the better

$$\forall k \in [1, L], s(k) = \begin{cases} \frac{\mu_{inter}(k) - \mu_{intra}(k)}{max(\mu_{inter}(k), \mu_{intra}(k))} & \text{if } |C_p| \geq 2 \\ 0 \text{ else} \end{cases}$$

Projection with a Silhouette Score of 0.49

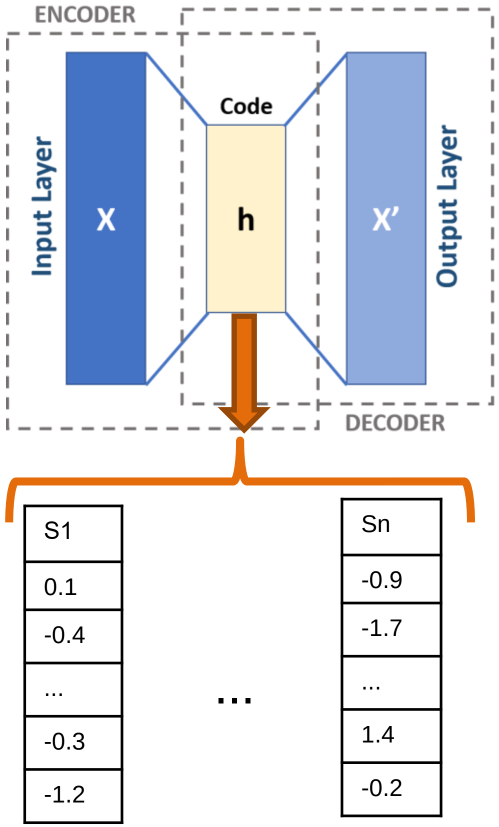


Projection with a Silhouette Score of -0.56



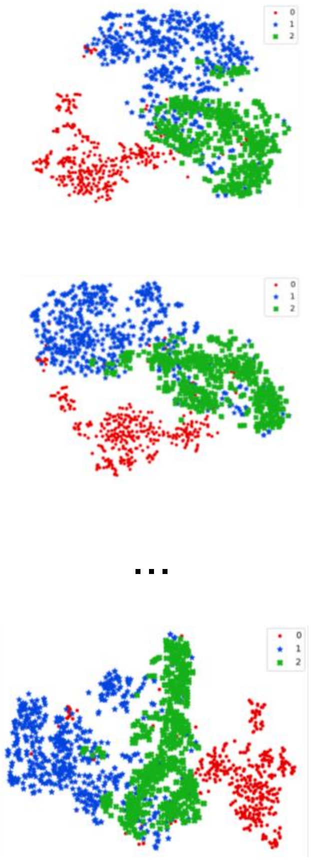
[1]Rousseeuw - 1987 - Silhouettes: A graphical aid to the interpretation and validation of cluster analysis

Dimensionality Reduction



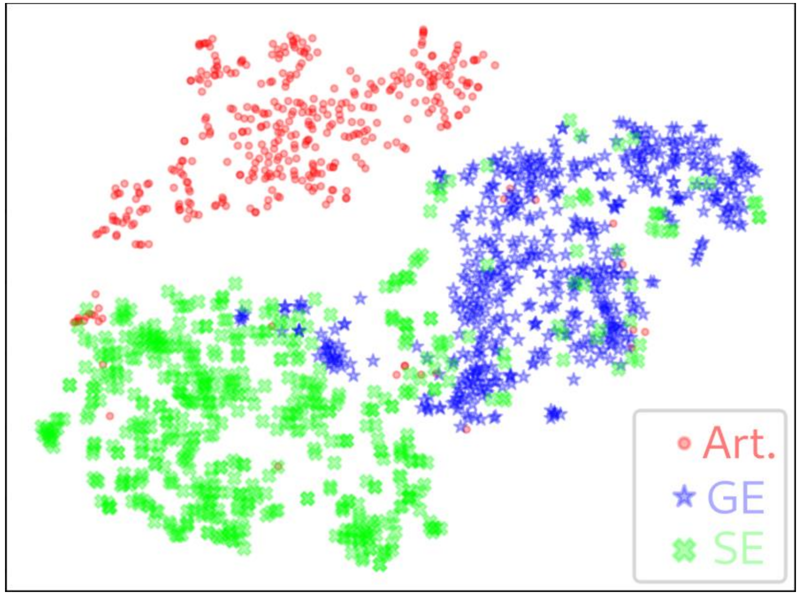
Features Dataset

t-SNE



Computed Projections
(3 t-SNE hyper-parameters)

Best Silhouette Score Selection



Selected projection for manual annotation and label propagation

Contribution 1.a.: Semi-automatic data annotation method **state-of-the-art comparison**

Considered neighborhood to propagate the labels

Minimal local quality threshold

Dataset	Propagation method	$\lvert\mathcal{L}\rvert$	$\lvert\mathcal{U}\rvert$	τ	K	Annotation accuracy	Final % of labeled samples (%)	Annotation time (ms/sample)
MNIST	Std-KNN	1496	13504	-	5	91.83 ± 1.47	95.39 ± 1.05	$(30.98 \pm 5.84) \times 10^{-3}$
	Std-KNN	1496	13504	-	10	90.74 ± 1.45	99.43 ± 0.23	$(\mathbf{28.78 \pm 5.13}) \times \mathbf{10^{-3}}$
	LQ-KNN	1496	13504	0.1	5	**93.12 ± 1.36**	93.88 ± 0.66	$(59.10 \pm 12.35) \times 10^{-3}$
	LQ-KNN	1496	13504	0.1	10	92.66 ± 1.30	98.16 ± 0.42	$(50.48 \pm 11.32) \times 10^{-3}$
	OPF-semi	1496	13504	-	-	82.32 ± 6.17	**100.0 ± 0.0**	102.71 ± 17.52
OrganCMNIST	Std-KNN	1534	13858	-	5	81.87 ± 0.76	90.26 ± 2.64	$(26.33 \pm 2.65) \times 10^{-3}$
	Std-KNN	1534	13858	-	10	79.86 ± 0.67	99.00 ± 0.20	$(\mathbf{23.41 \pm 1.98}) \times \mathbf{10^{-3}}$
	LQ-KNN	1534	13858	0.1	5	**84.46 ± 0.57**	85.62 ± 1.99	$(53.00 \pm 7.47) \times 10^{-3}$
	LQ-KNN	1534	13858	0.1	10	82.73 ± 0.44	96.24 ± 1.09	$(44.36 \pm 5.69) \times 10^{-3}$
	OPF-semi	1534	13858	-	-	75.22 ± 4.48	**100.0 ± 0.0**	86.52 ± 0.51
HITS	Std-KNN	152	1393	-	5	82.12 ± 2.37	95.99 ± 1.70	$(10.39 \pm 0.20) \times 10^{-2}$
	Std-KNN	152	1393	-	10	81.36 ± 1.81	99.58 ± 0.63	$(\mathbf{10.04 \pm 0.18}) \times \mathbf{10^{-2}}$
	LQ-KNN	152	1393	0.1	5	**82.84 ± 2.12**	94.48 ± 1.72	$(16.87 \pm 0.48) \times 10^{-3}$
	LQ-KNN	152	1393	0.1	10	82.67 ± 2.02	98.50 ± 0.80	$(16.13 \pm 0.35) \times 10^{-2}$
	OPF-semi	152	1393	-	-	78.40 ± 13.44	**100.0 ± 0.0**	9.48 ± 1.1

Table – Label propagation methods comparison on different datasets

Metrics:

Annotation accuracy:

$$\frac{\text{\# correct new labeled samples}}{\text{\# new labeled samples}}$$

Percentage of new labeled samples:

$$\frac{\text{\# new labeled samples}}{\text{\# originally unlabeled samples}}$$

Contribution 1.b: Optimal 2D projection selection.

Dataset: HITS Dataset.

Evaluation: Label Propagation on 2 different projections.

Metrics: Annotation accuracy and percentage of new labeled samples.

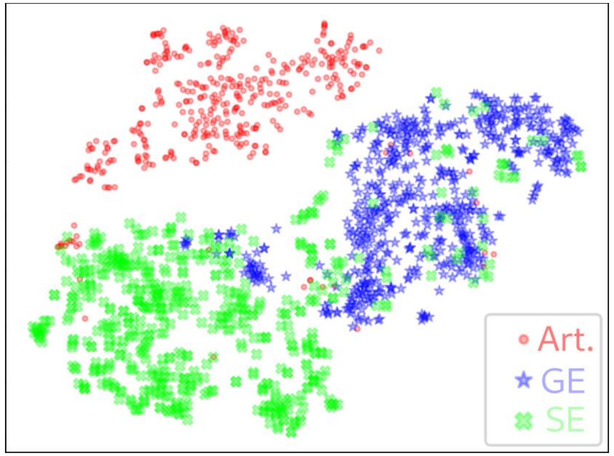
Results:

K	Propagation method	Projection	$\lvert\mathcal{L}\rvert$	$\lvert\mathcal{U}\rvert$	τ	Annotation accuracy	Final % of labeled samples
5	**Std-KNN**	**Best**	**152**	**1393**	**-**	$\mathbf{89.8 \pm 1.63}$	$\mathbf{95.52 \pm 1.23}$
	Std-KNN	Worst	152	1393	-	52.2 ± 2.53	98.78 ± 0.42
5	**LQ-KNN**	**Best**	**152**	**1393**	**0.1**	$\mathbf{90.23 \pm 1.46}$	$\mathbf{94.93 \pm 1.32}$
	LQ-KNN	Worst	152	1393	0.1	70.69 ± 2.64	57.4 ± 2.01

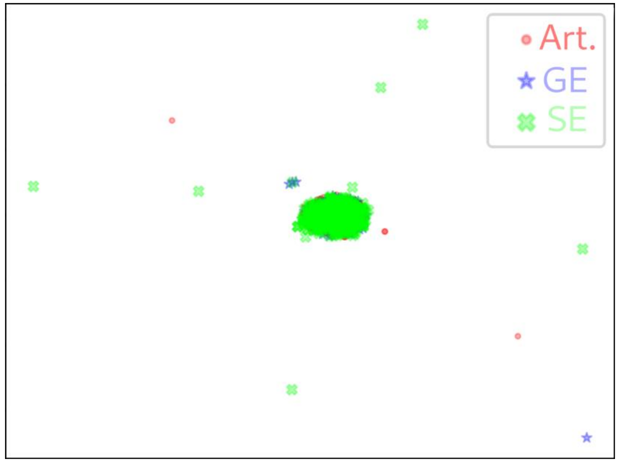
Conclusion:

- Projection selection improves annotation accuracy.
- Our proposed method is more robust against bad projections.

Best Projection



Worst Projection



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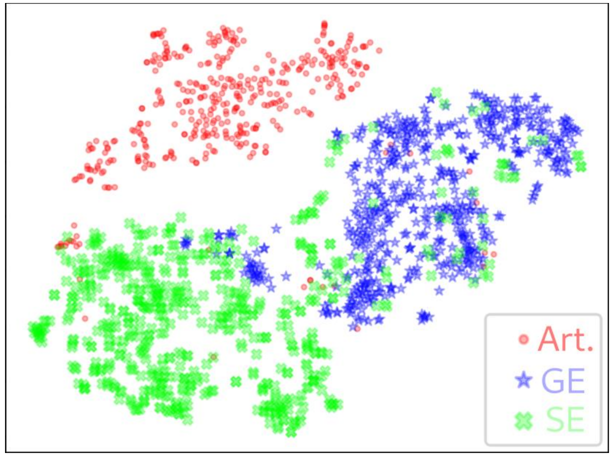
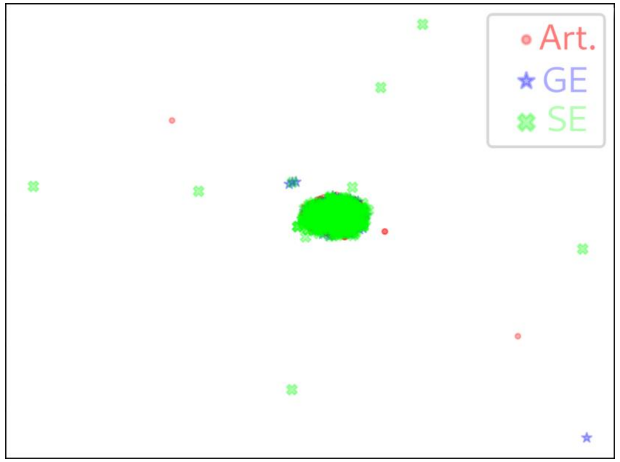


Worst Projection



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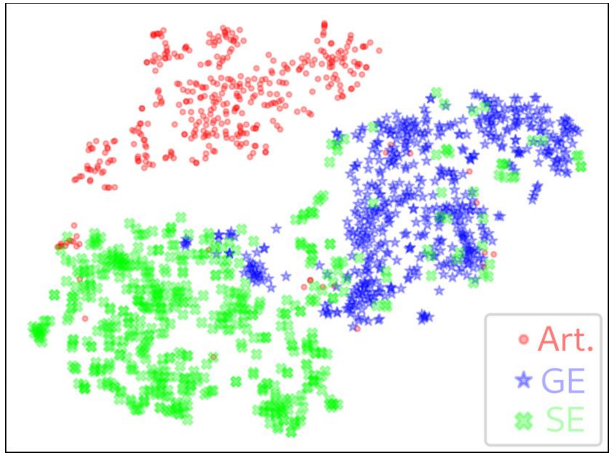
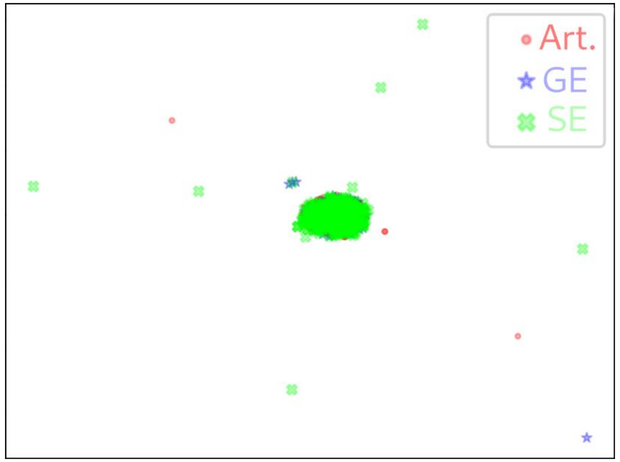
	LQ-KNN	Worst	152	1393	0.1	70.69 ± 2.64	57.4 ± 2.01

Conclusion:
- Projection selection improves annotation accuracy.
- Our proposed method is more robust against bad projections.

Best Projection



Worst Projection



Contribution 1.c: Classification using robust loss functions to compensate the noise in the labels.

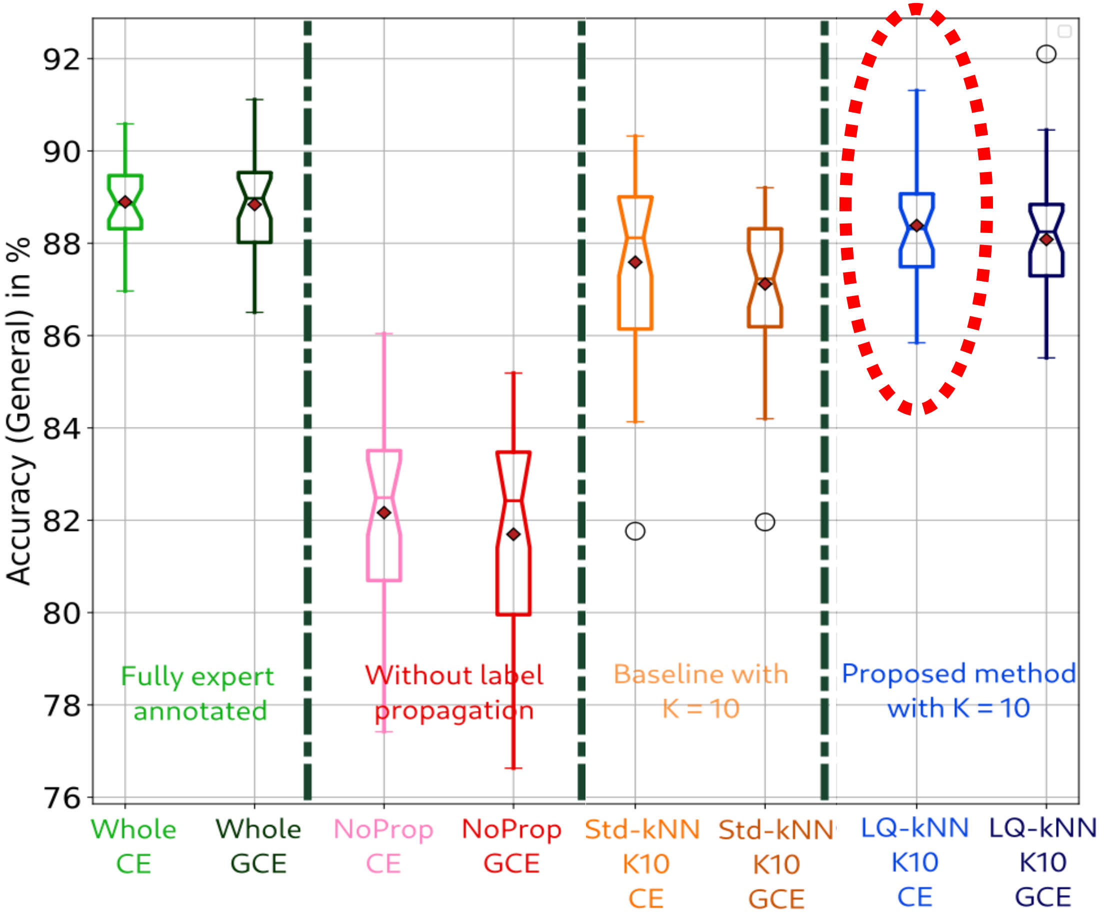
Datasets

Dataset	Core Dataset	Prop. method	$\vert\mathcal{L}\vert$	$\vert\mathcal{U}\vert$	# of automatically labeled samples	Mean annot. accuracy	K	τ
HITS No Prop.	HITS	No Prop.	152	1393	-	-	-	-
HITS Whole		No Prop.	1545	0	-	-	-	-
HITS Std-KNN-K10		Std-KNN			1390 ± 2	88.72 ± 2.33	10	-
HITS LQ-KNN-K10		LQ-KNN			1382 ± 3	89.92 ± 1.42	10	0.1

Metrics:

Classification accuracy.
Classification class accuracy.

==> Our method allows to increase the classification accuracy by 6 % with respect to using a reduced dataset (no propagation)



HITS Datasets Results General Accuracy

Database Creation

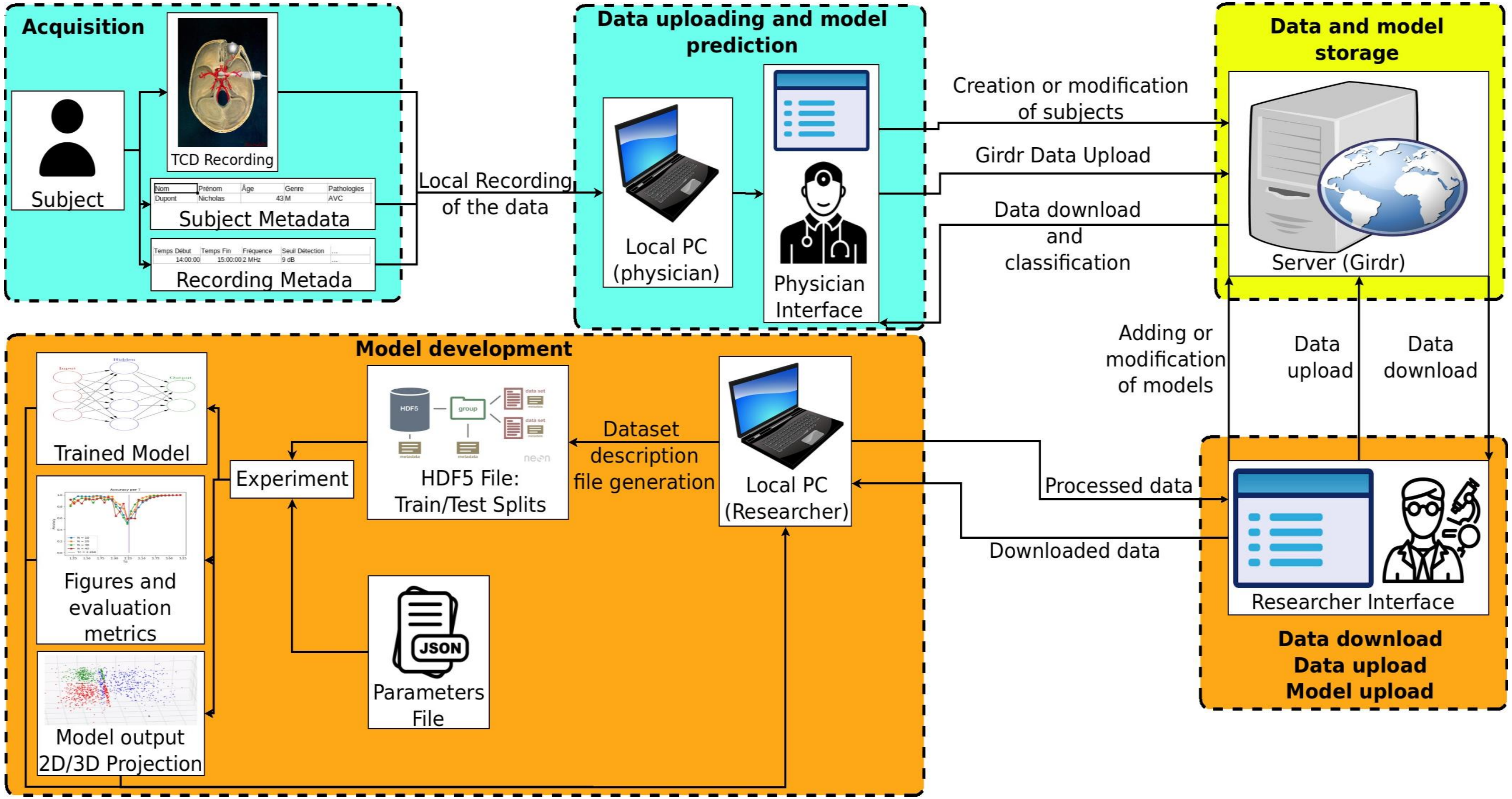


Figure – Data pipeline. Two types of data : raw and derivative.

Database Structure

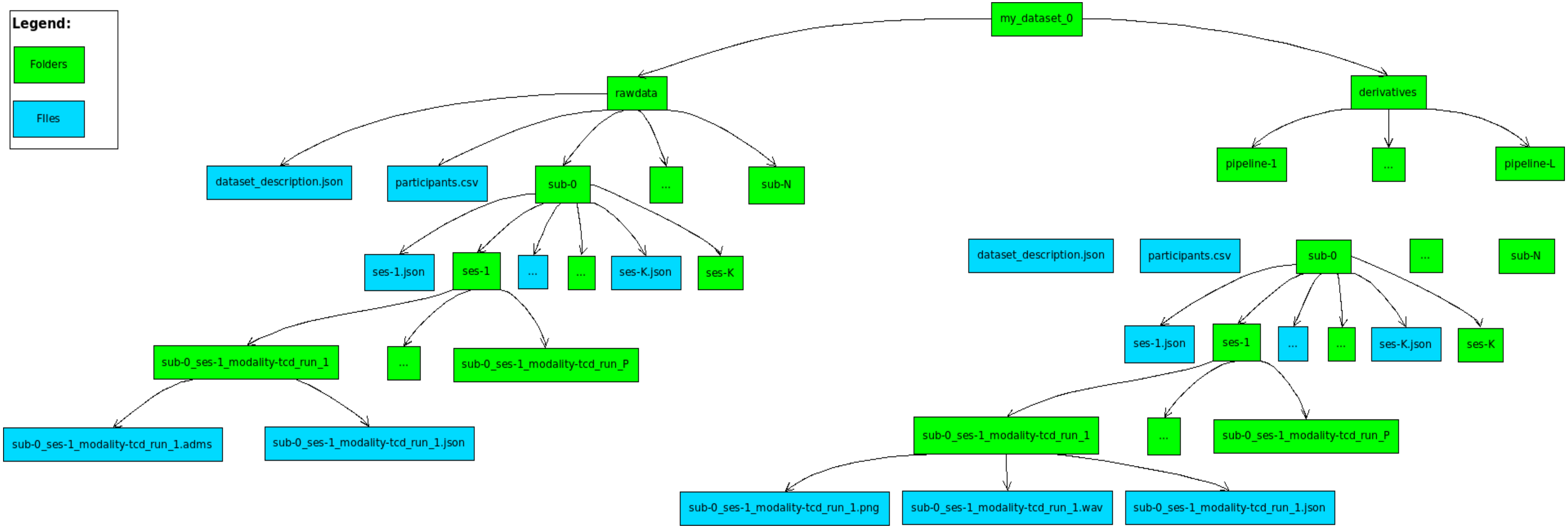


Figure – Database structure on Gridr

Auto-encoders architectures

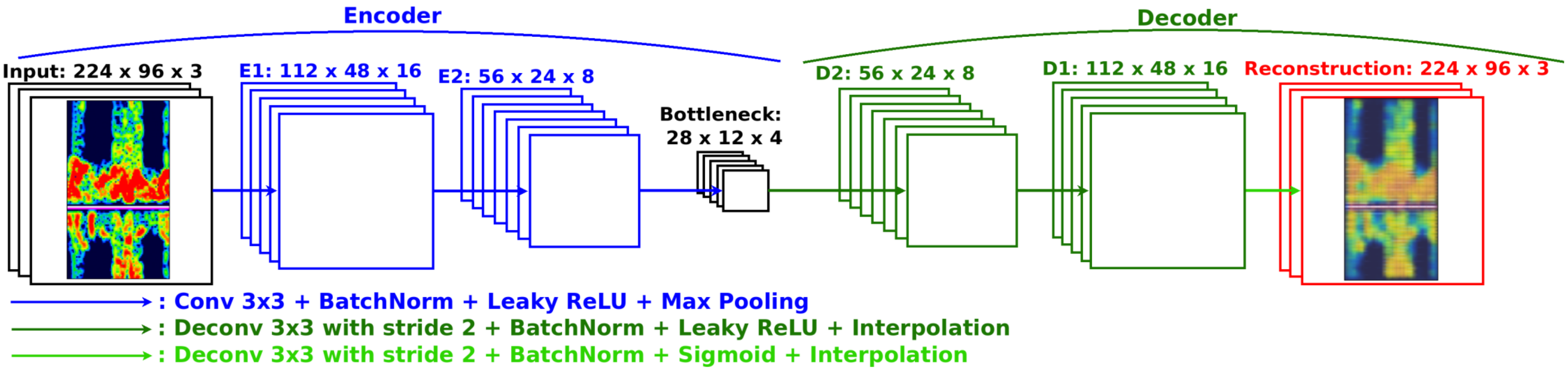


Figure – Convolutional auto-encoder for the HITS dataset.

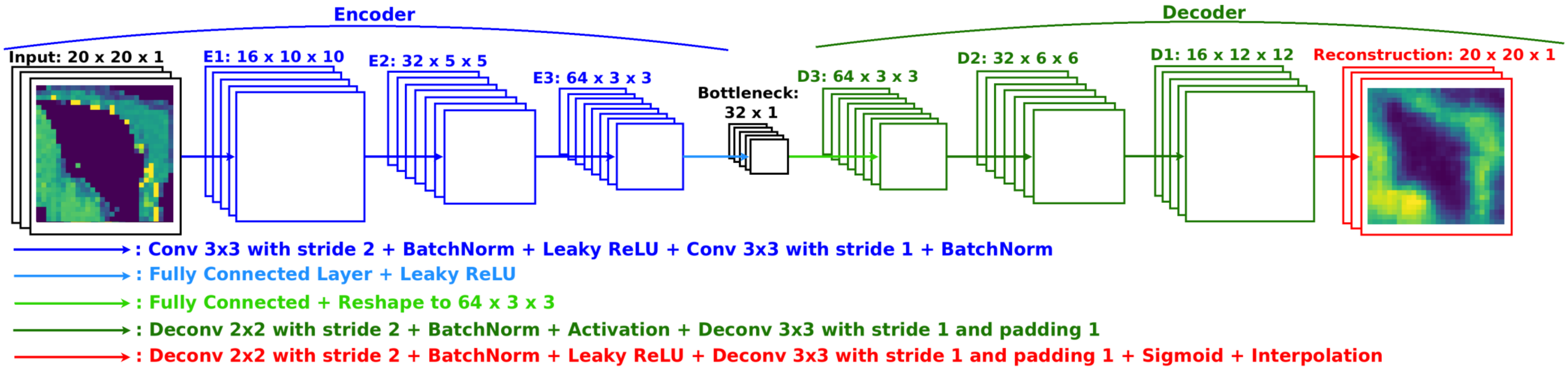


Figure – Convolutional auto-encoder for the OrganCMNIST and MNIST datasets.

Classifiers architectures

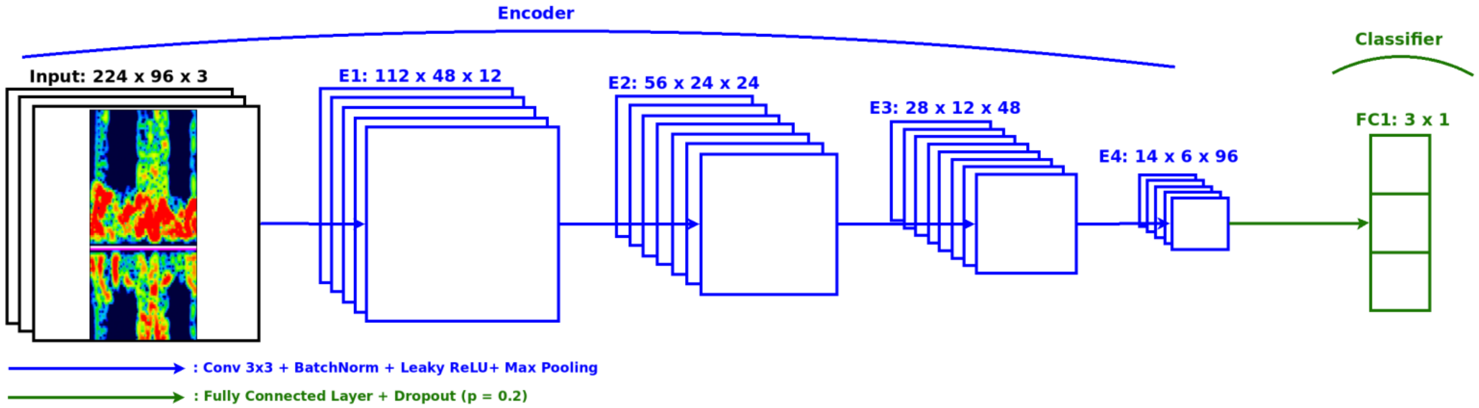


Figure – Convolutional classifier for the HITS dataset.

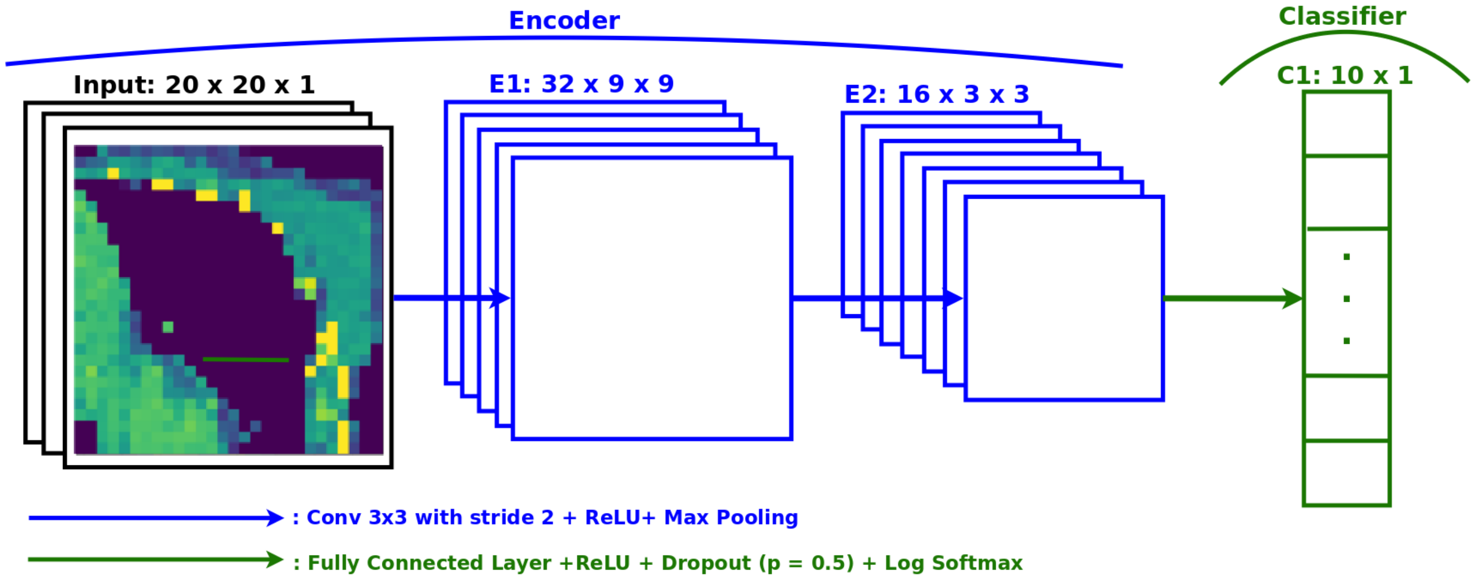


Figure – Convolutional classifier for the OrganCMNIST and MNIST

Semi-automatic data annotation

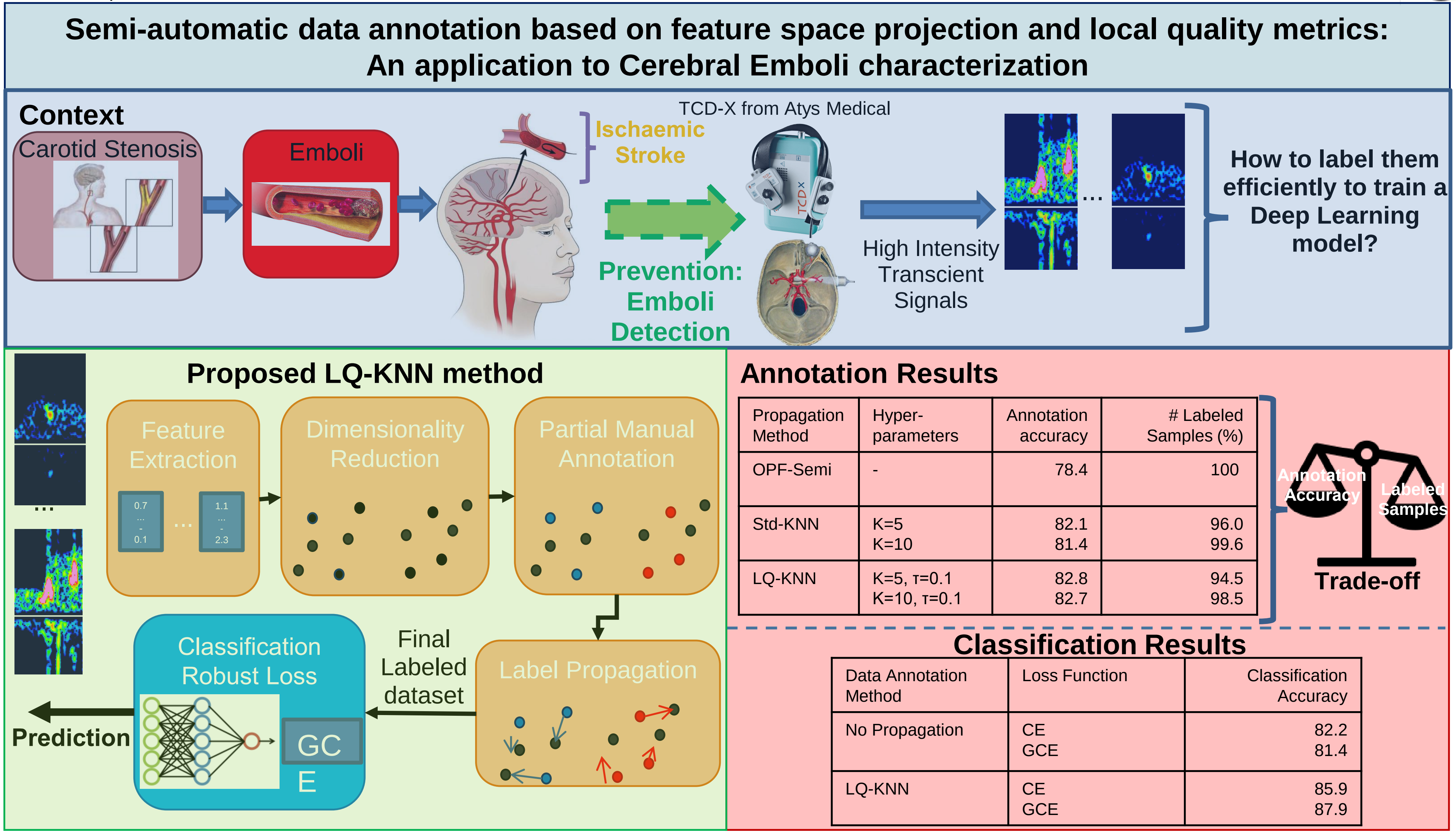


FIGURE - Graphical abstract of Vindas et al. (2022) in Medical Image Analysis

Contribution 2 : Multi-feature medical signal classification

ECG 1D CNN-transformer

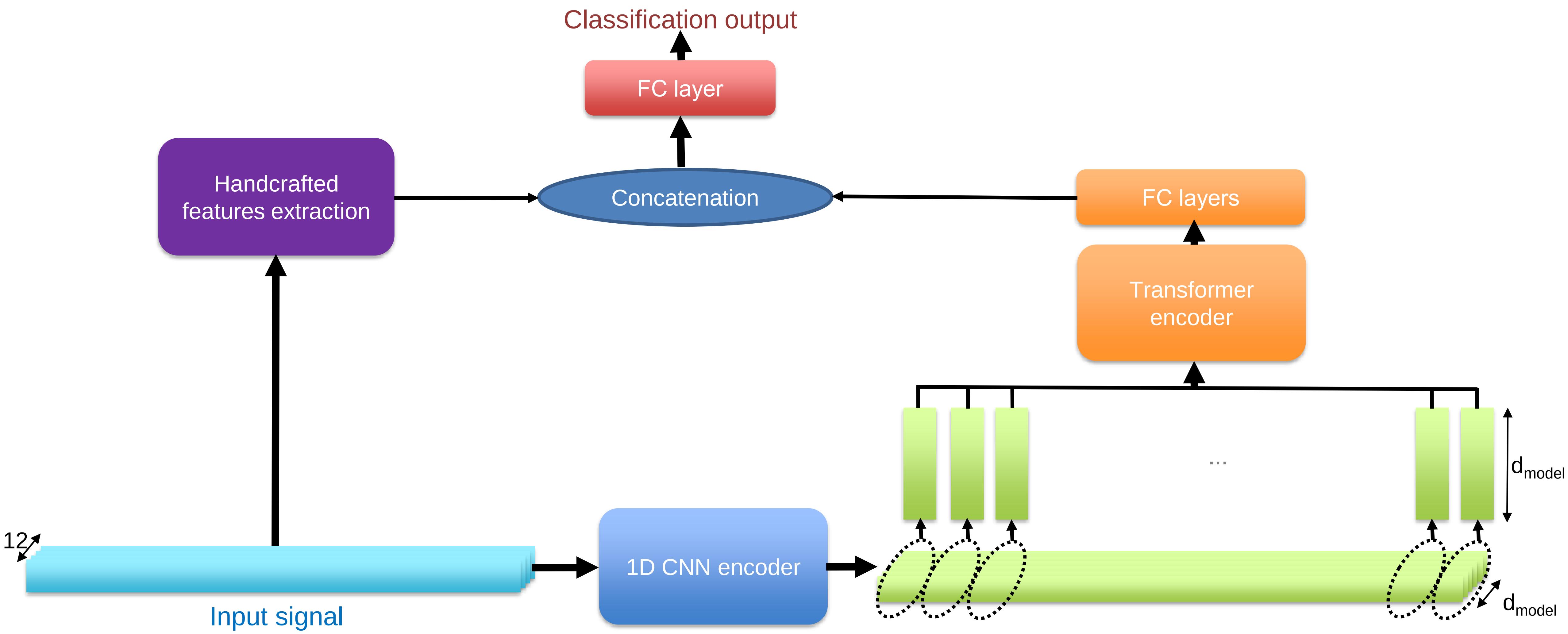


Figure - Proposed 1D CNN-transformer model for ECG signal classification (**Natarajan et al., 2020.**)

Link constraints regularization

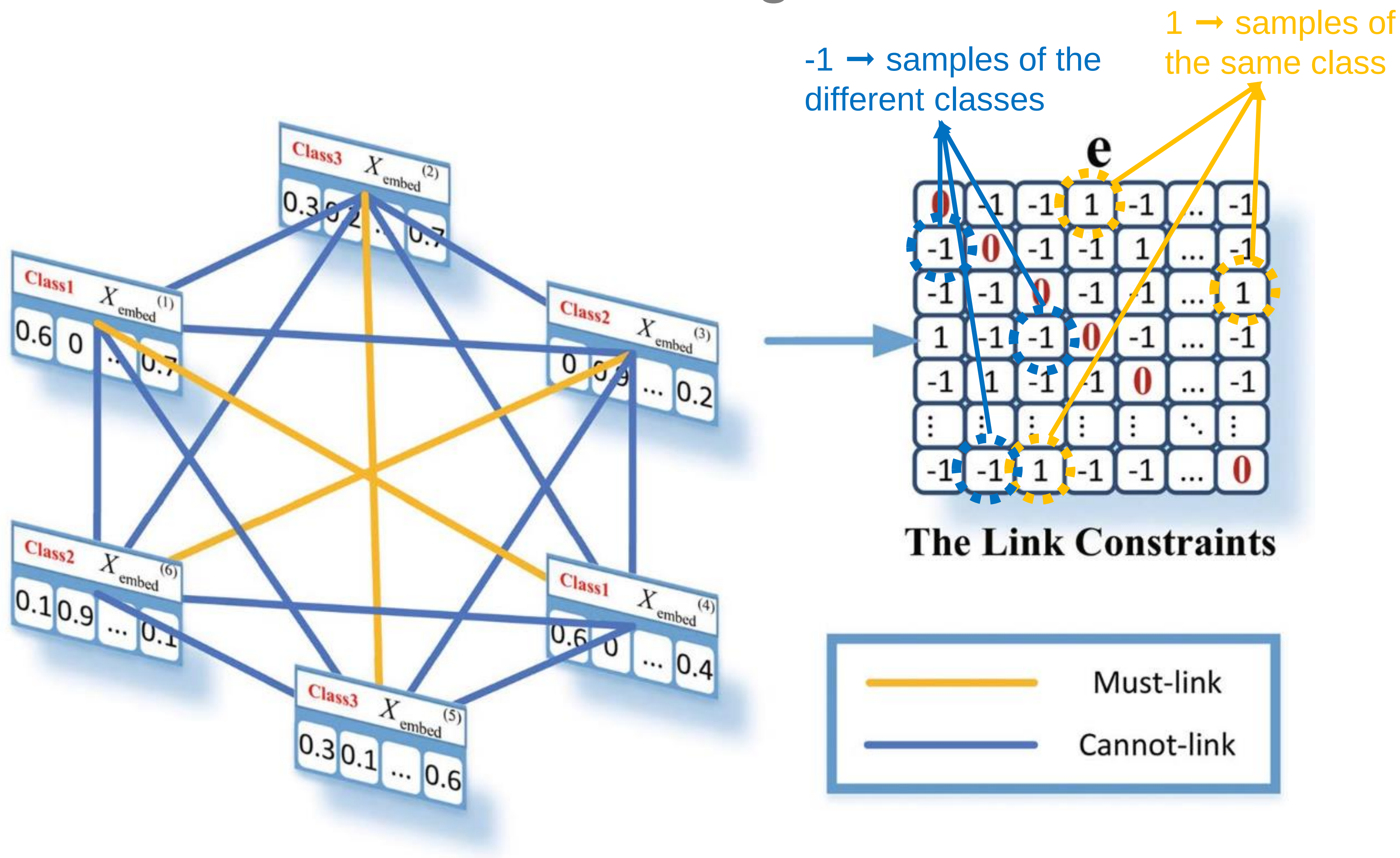
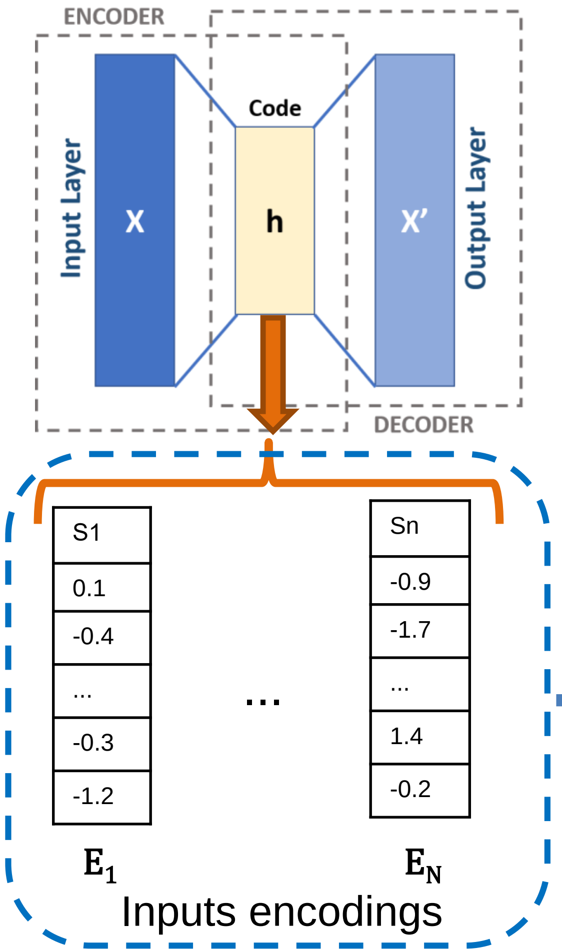


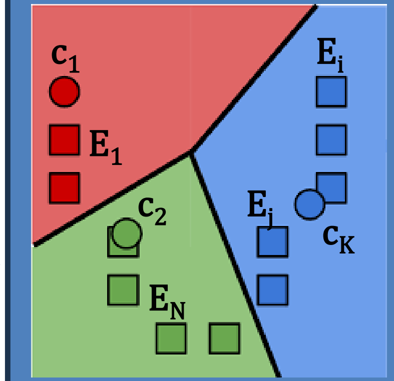
Figure – Links constraints regularization illustration for transformer models (**Che et al., 2021**)

Deep embedded clustering (**DEC**)



Clustering

Initialization



K-means

Soft assignments of E_i to C_j

$$q_{ij} = \frac{\sum_{p=1}^{J}\left(1+\frac{||\mathcal{E}(X_i)-\mathbf{c}_p||^2}{\alpha}\right)^{\frac{\alpha+1}{2}}}{\left(1+\frac{||\mathcal{E}(X_i)-\mathbf{c}_j||^2}{\alpha}\right)^{\frac{\alpha+1}{2}}}$$

Clusters soft frequencies

$$f_j = \sum_{p=1}^{J} q_{pj}$$

Target distribution

$$p_{ij} = \frac{\frac{q_{ij}^2}{f_j}}{\sum_{p=1}^{J}\frac{q_{ip}^2}{f_p}}$$

Properties
- Cluster purity.
- Focus on high confidence samples.
- Normalization of the contribution of each centroid to the final loss.

Deep embedded clustering (DEC) loss function

$$\mathcal{L}_{DEC} = KL(P||Q)$$

Figure – Deep embedded clustering (**DEC**) for unsupervised learning (**Xie et al., 2016**)

Single feature raw signal 1D CNN-transformer

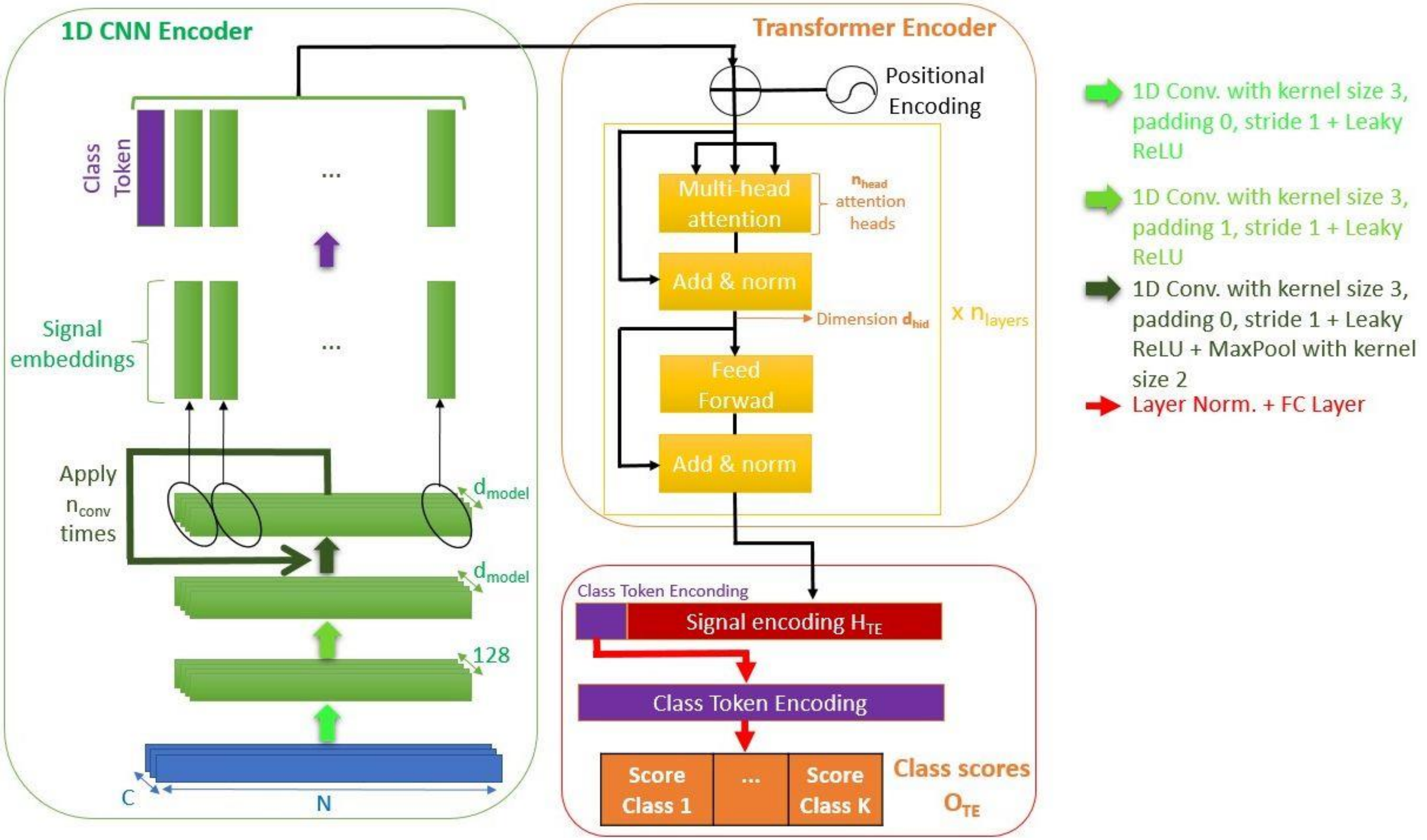


Figure - Proposed 1D CNN Transformer architecture (inspired from Natarajan et al. 2020).

Single feature raw signal 1D CNN-transformer

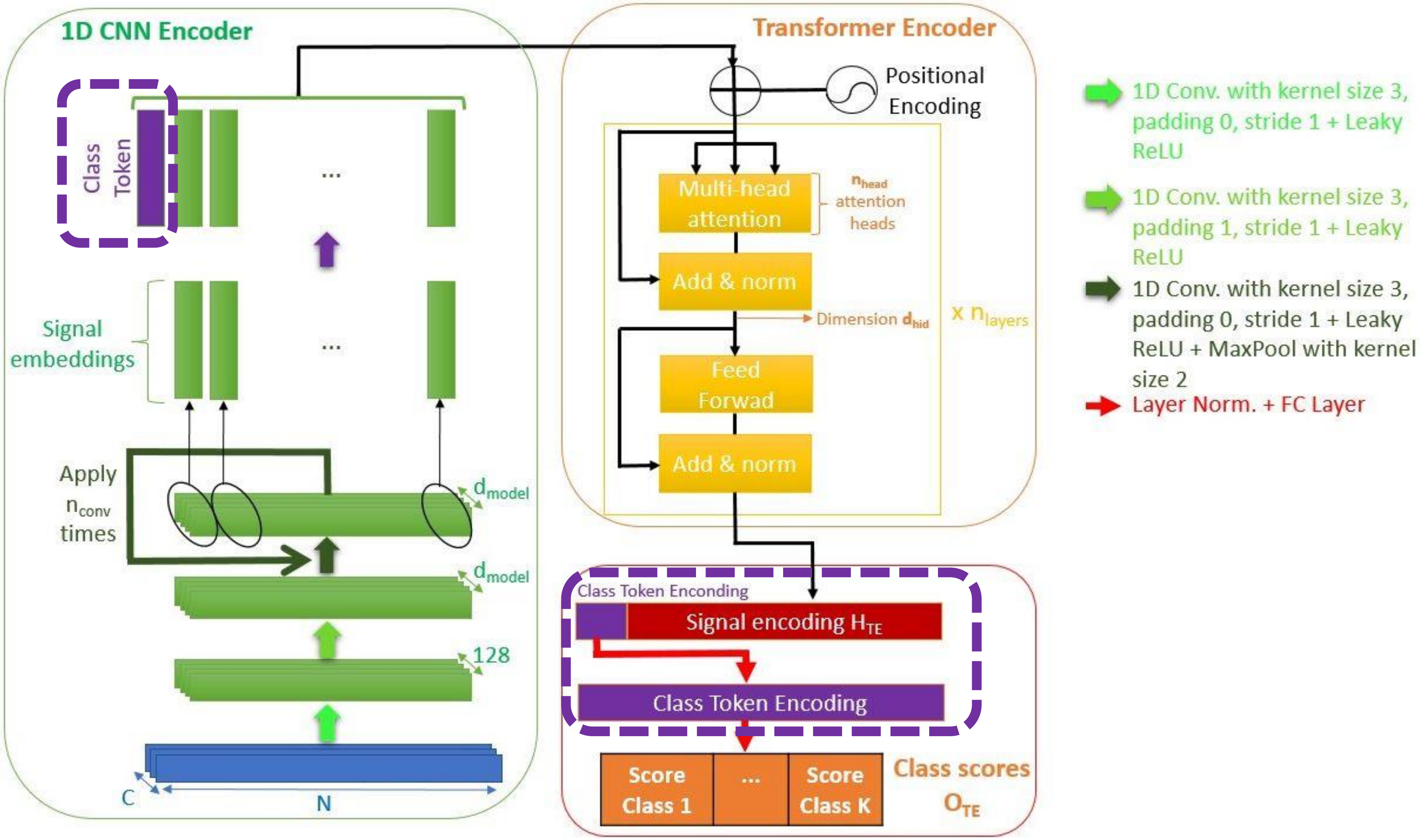
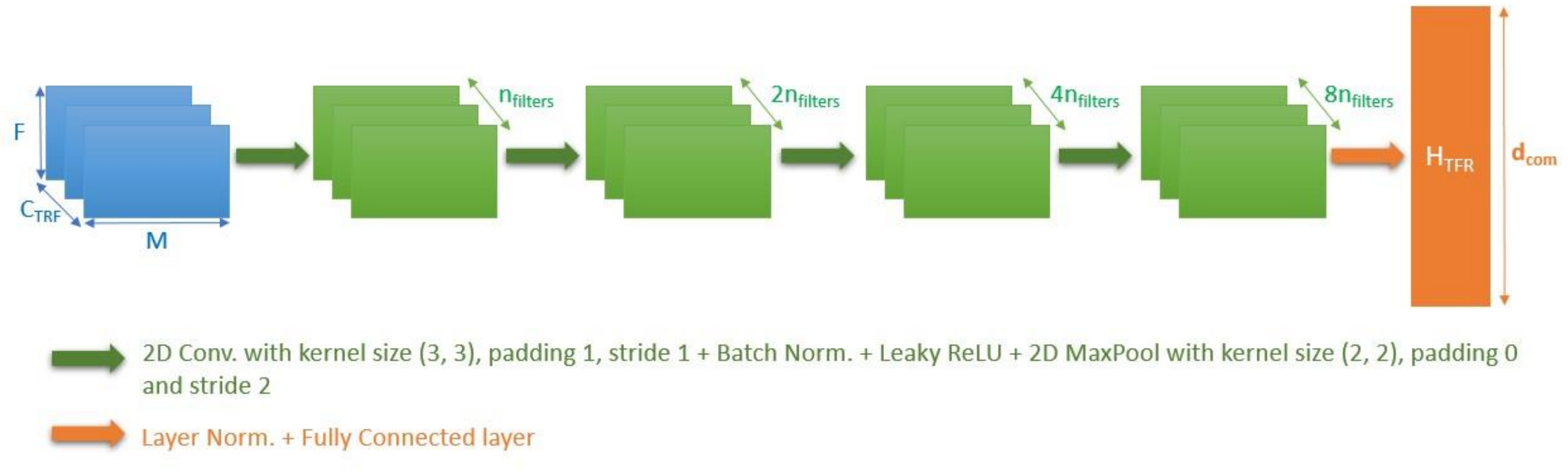
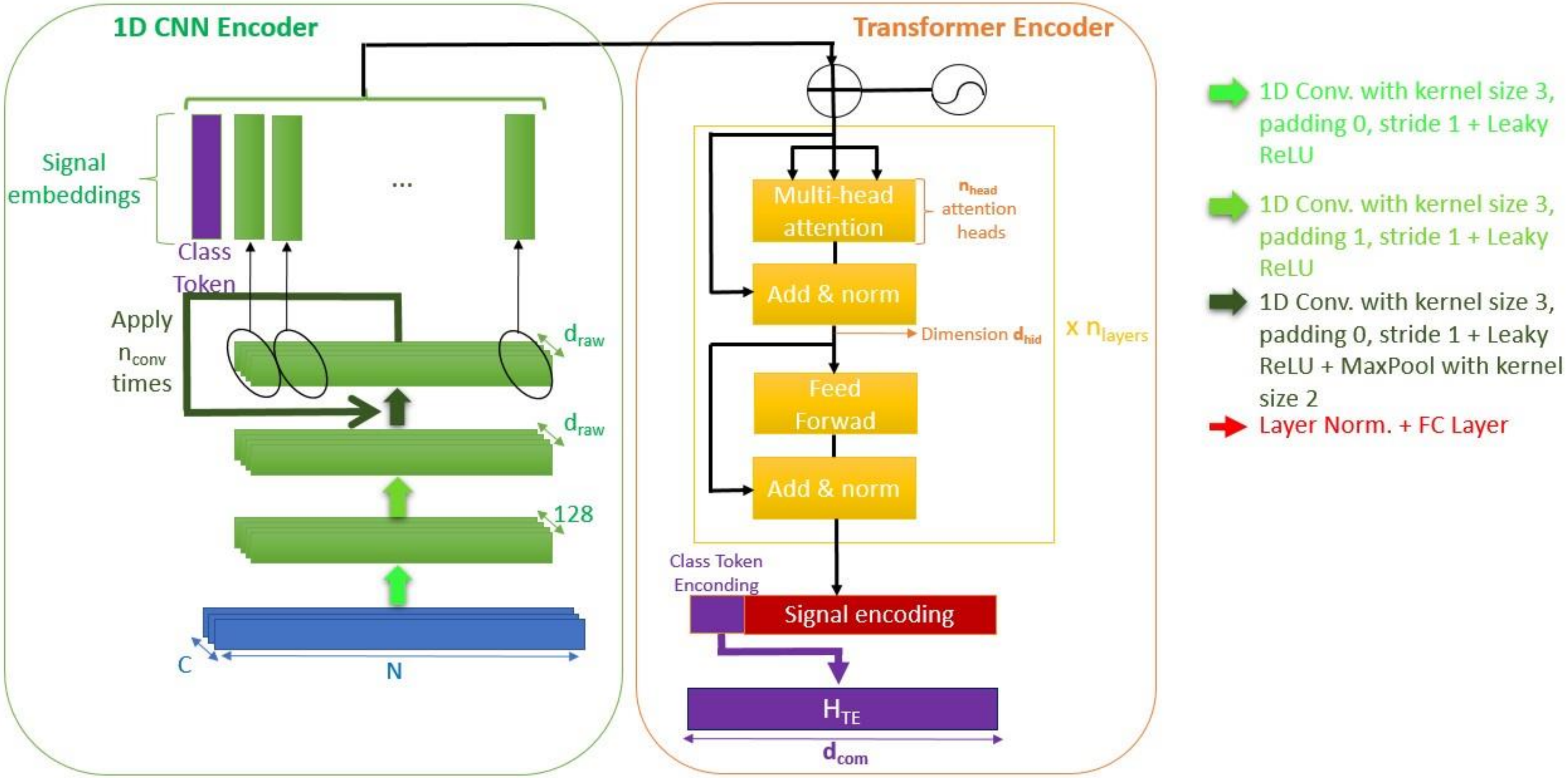


Figure - Proposed 1D CNN Transformer architecture (inspired from Natarajan et al. 2020).

CNN model late fusion approach



Transformer model intermediate fusion approach



Inspired from Natarajan et al. (2020), A wide and deep transformer neural network for 12-lead ecg classification.

CNN model intermediate fusion approach

2D Conv. with kernel size (3, 3), padding 1, stride 1 + Batch Norm. + Leaky ReLU + 2D MaxPool with kernel size (2, 2), padding 0 and stride 2

Layer Norm. + Fully Connected layer

Late fusion attention weights

Figure - Proposed hybrid CNN Transformer global model

Late fusion attention weights

Figure - Proposed hybrid CNN Transformer global model

Late fusion attention weights

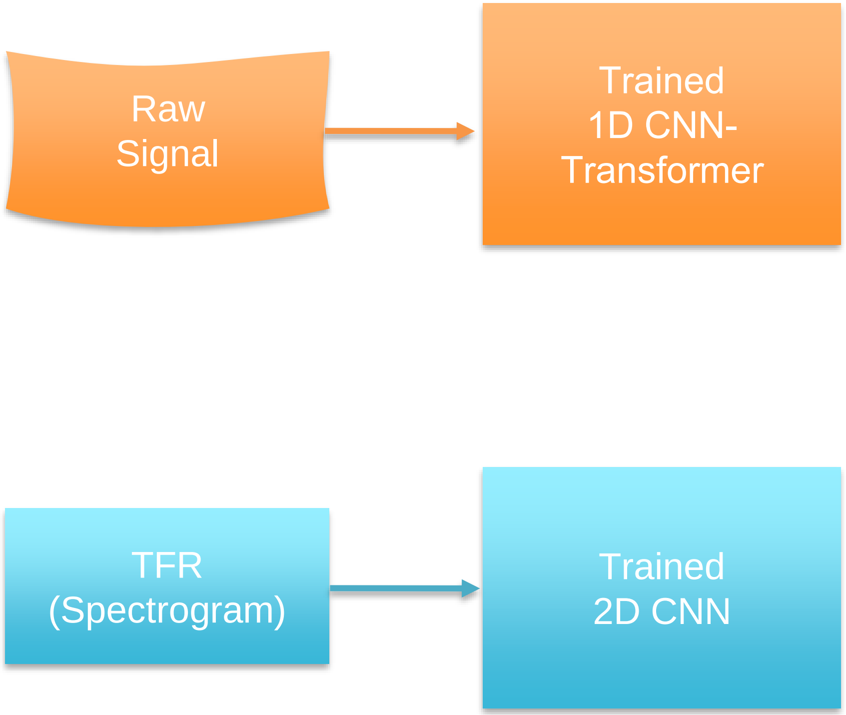


Figure - Proposed hybrid CNN Transformer global model

Late fusion attention weights

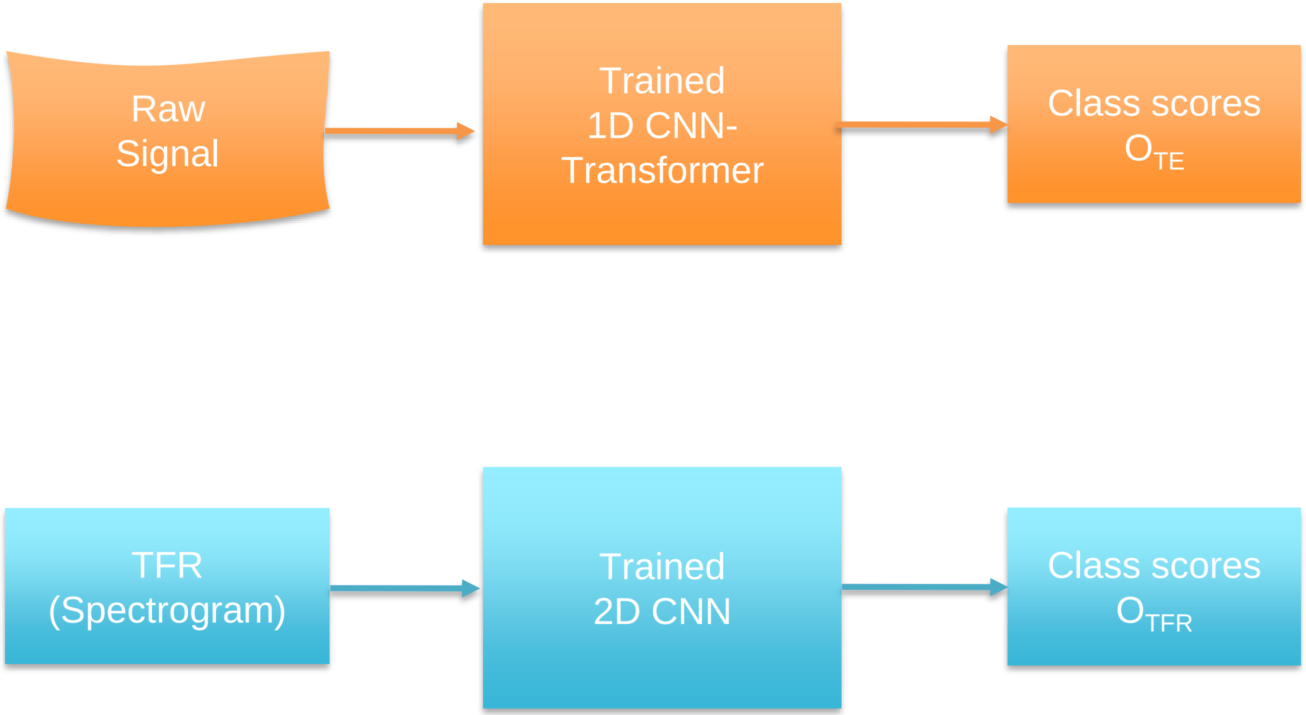


Figure - Proposed hybrid CNN Transformer global model

Late fusion attention weights

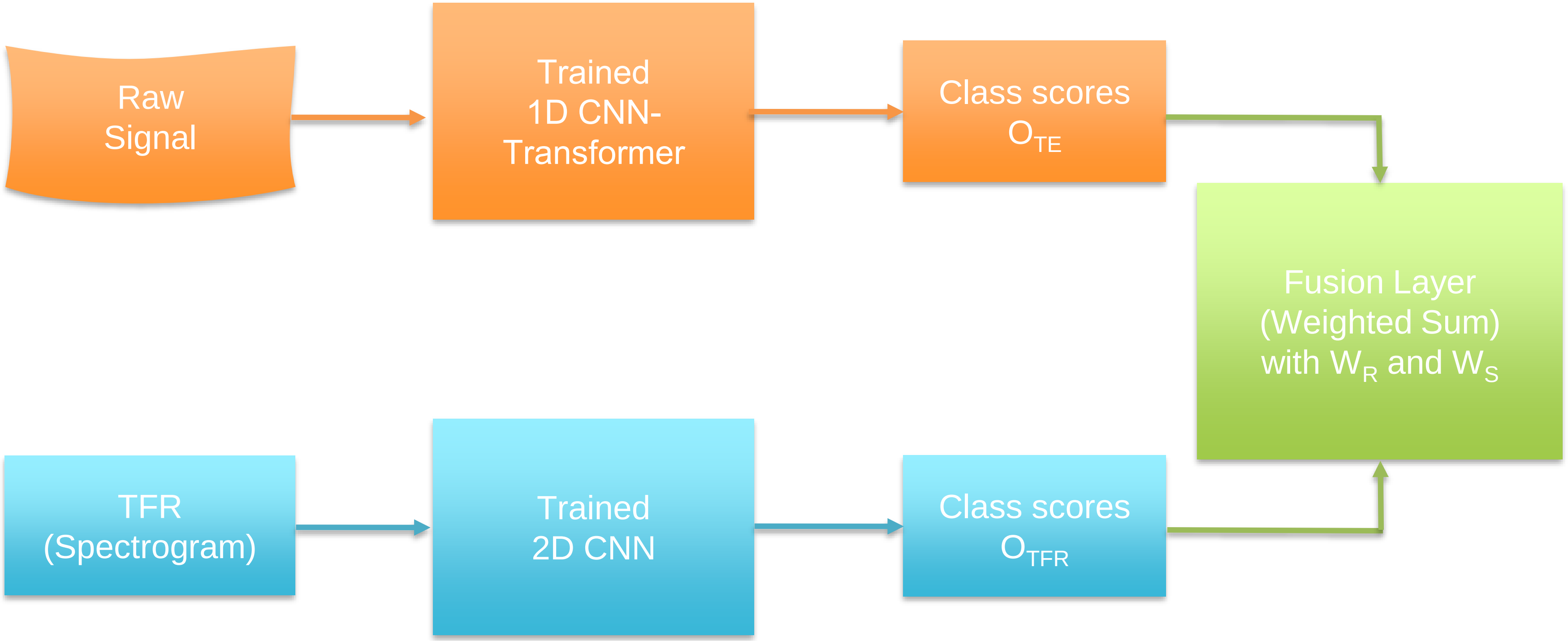


Figure - Proposed hybrid CNN Transformer global model

Late fusion attention weights

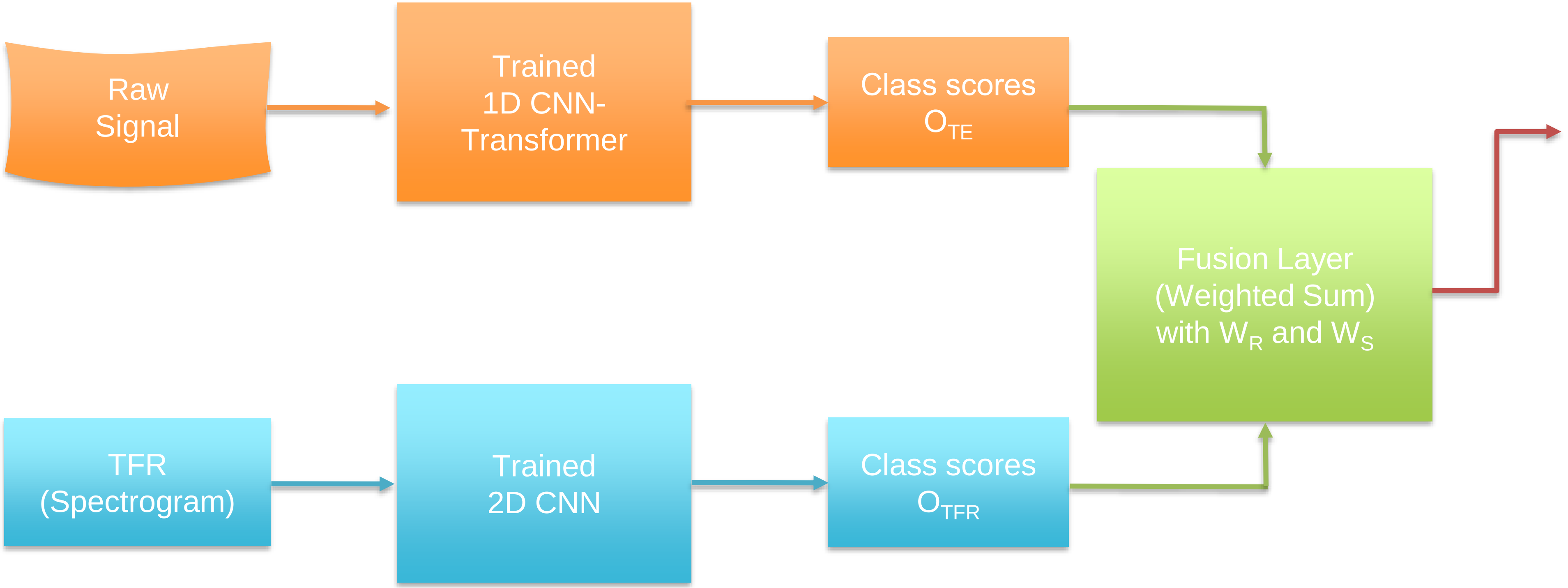


Figure - Proposed hybrid CNN Transformer global model

Late fusion attention weights

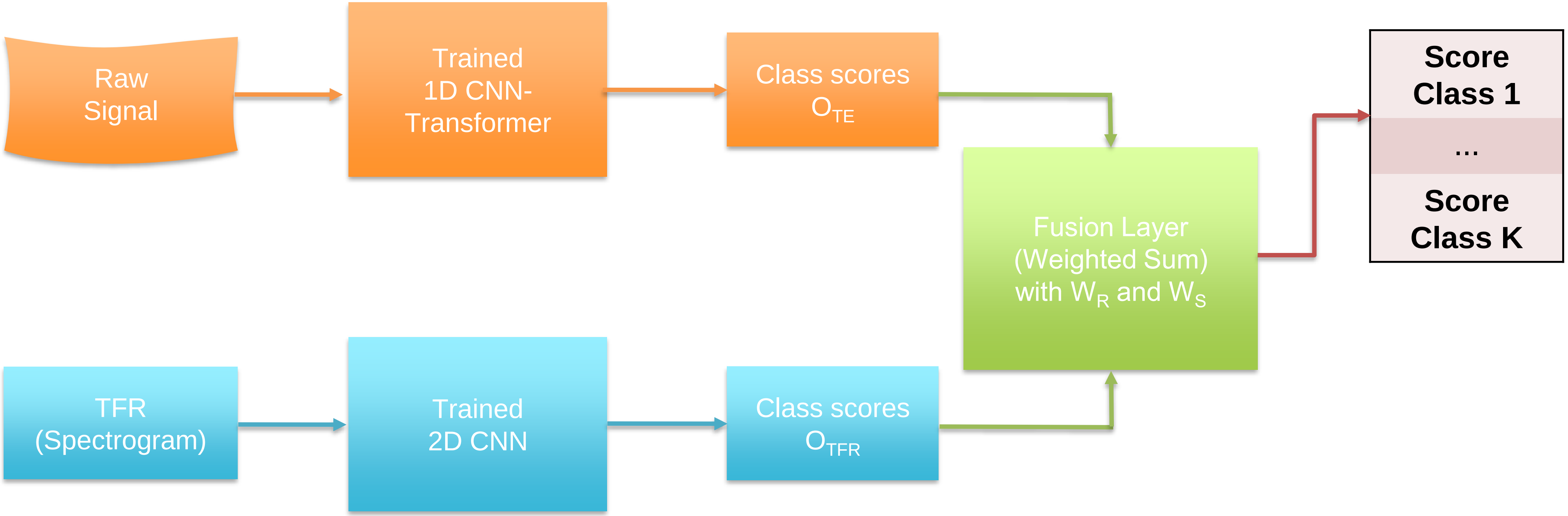


Figure - Proposed hybrid CNN Transformer global model

Late fusion attention weights

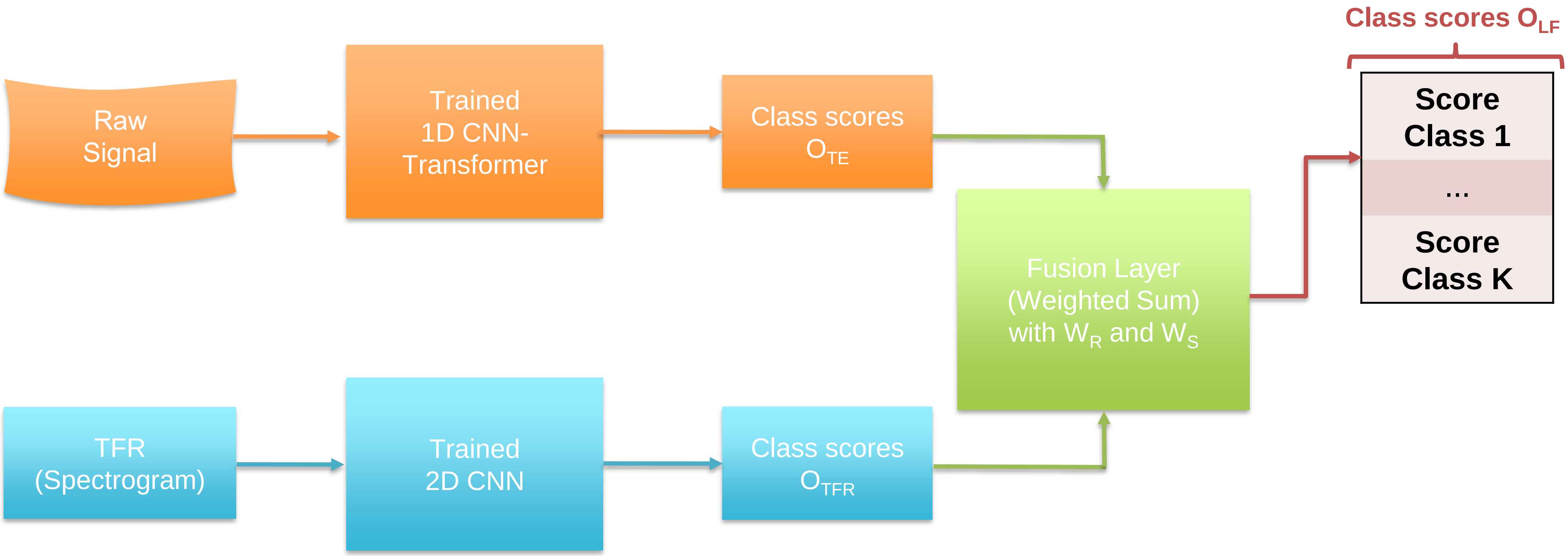


Figure - Proposed hybrid CNN Transformer global model

Late fusion attention weights

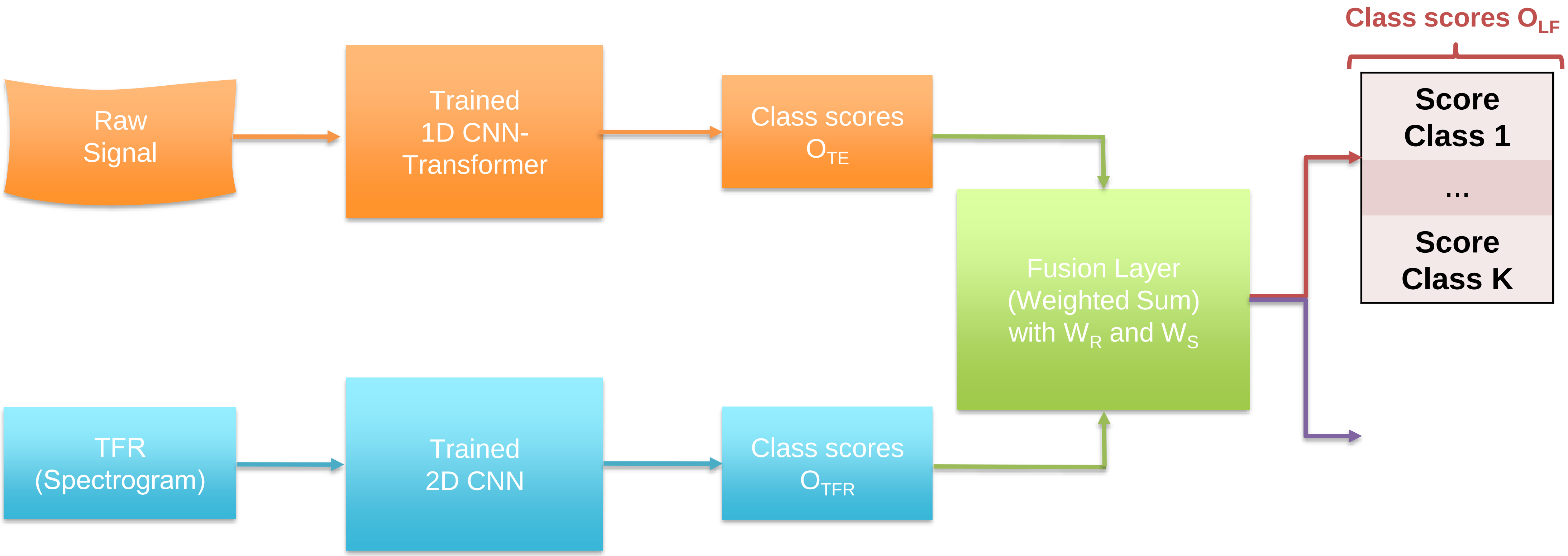


Figure - Proposed hybrid CNN Transformer global model

Late fusion attention weights

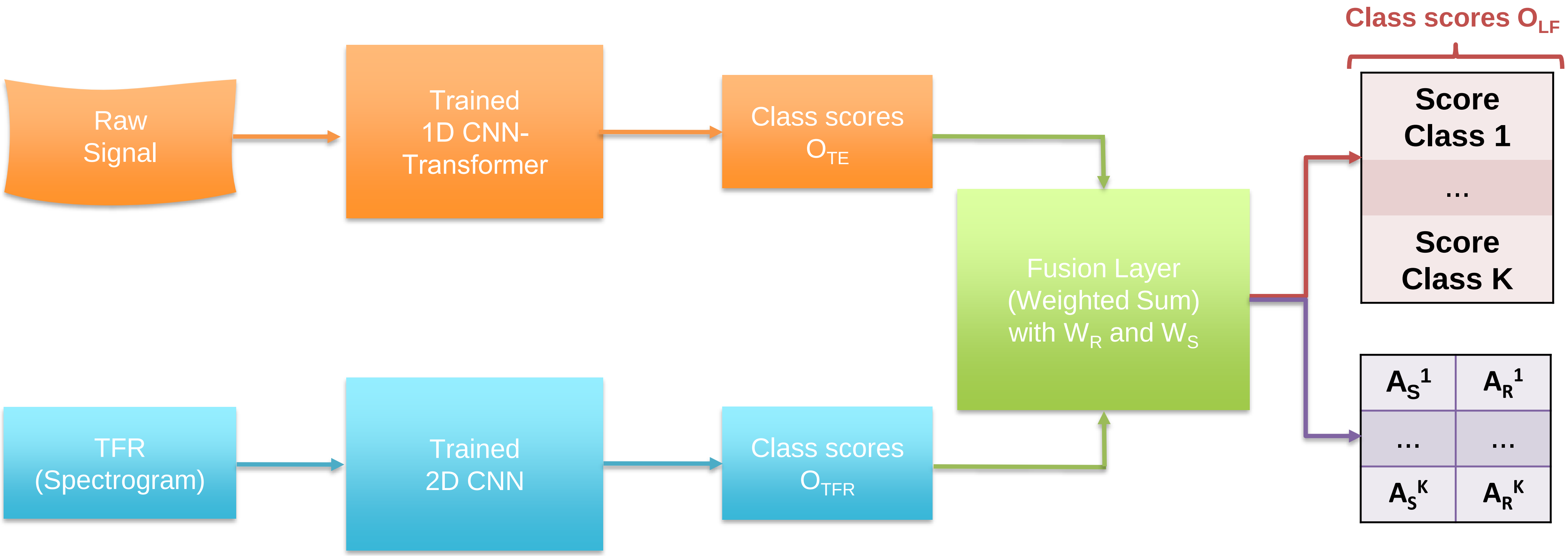


Figure - Proposed hybrid CNN Transformer global model

Late fusion attention weights

Figure - Proposed hybrid CNN Transformer global model

Late fusion attention weights

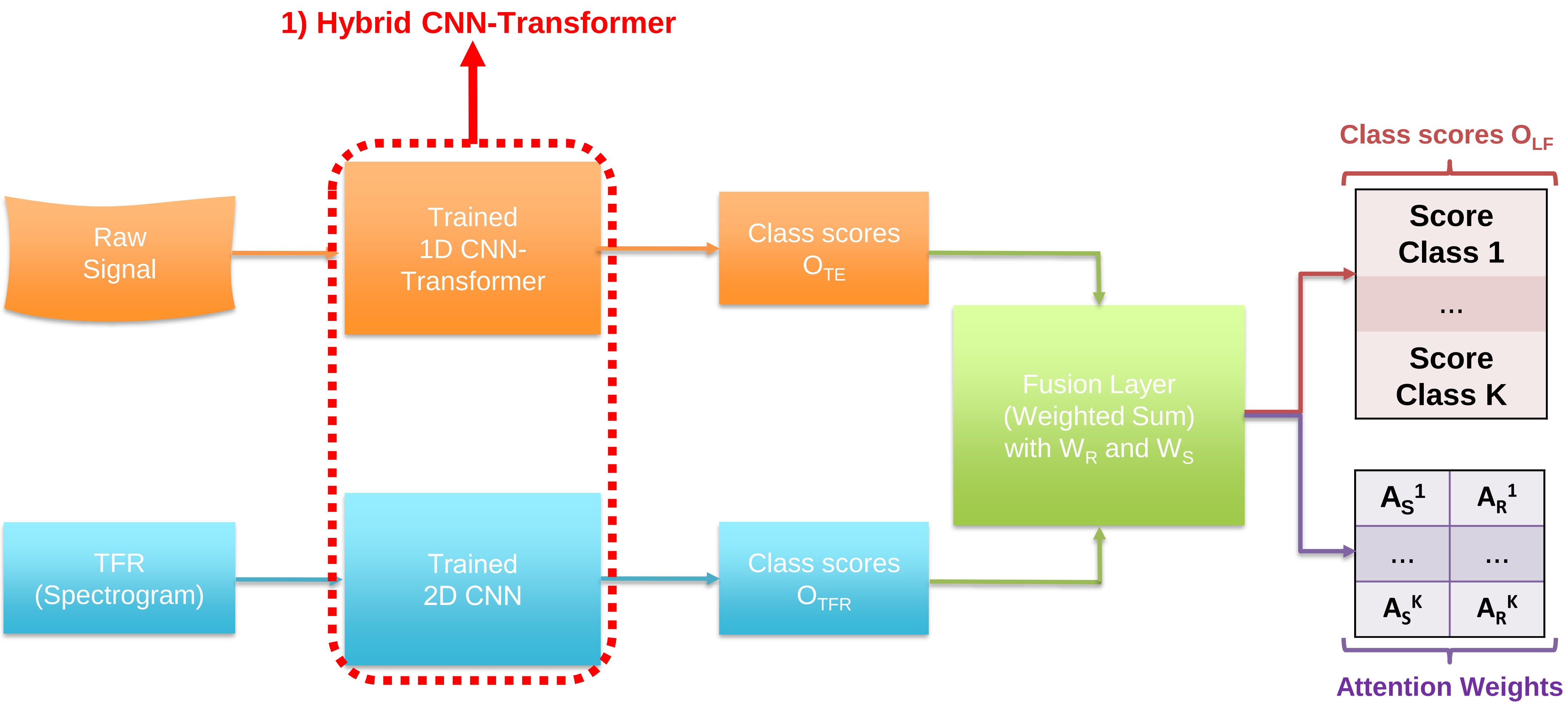


Figure - Proposed hybrid CNN Transformer global model

Late fusion attention weights

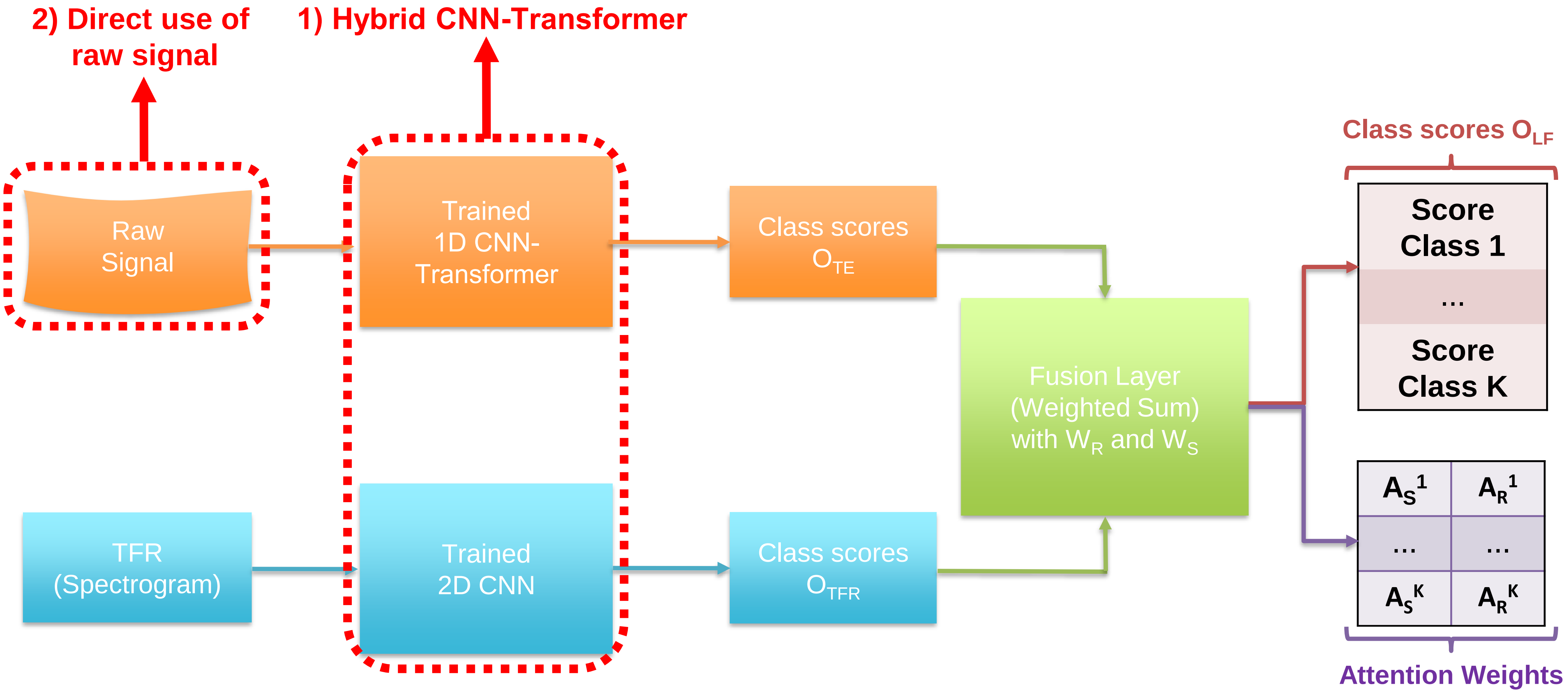


Figure - Proposed hybrid CNN Transformer global model

Late fusion attention weights

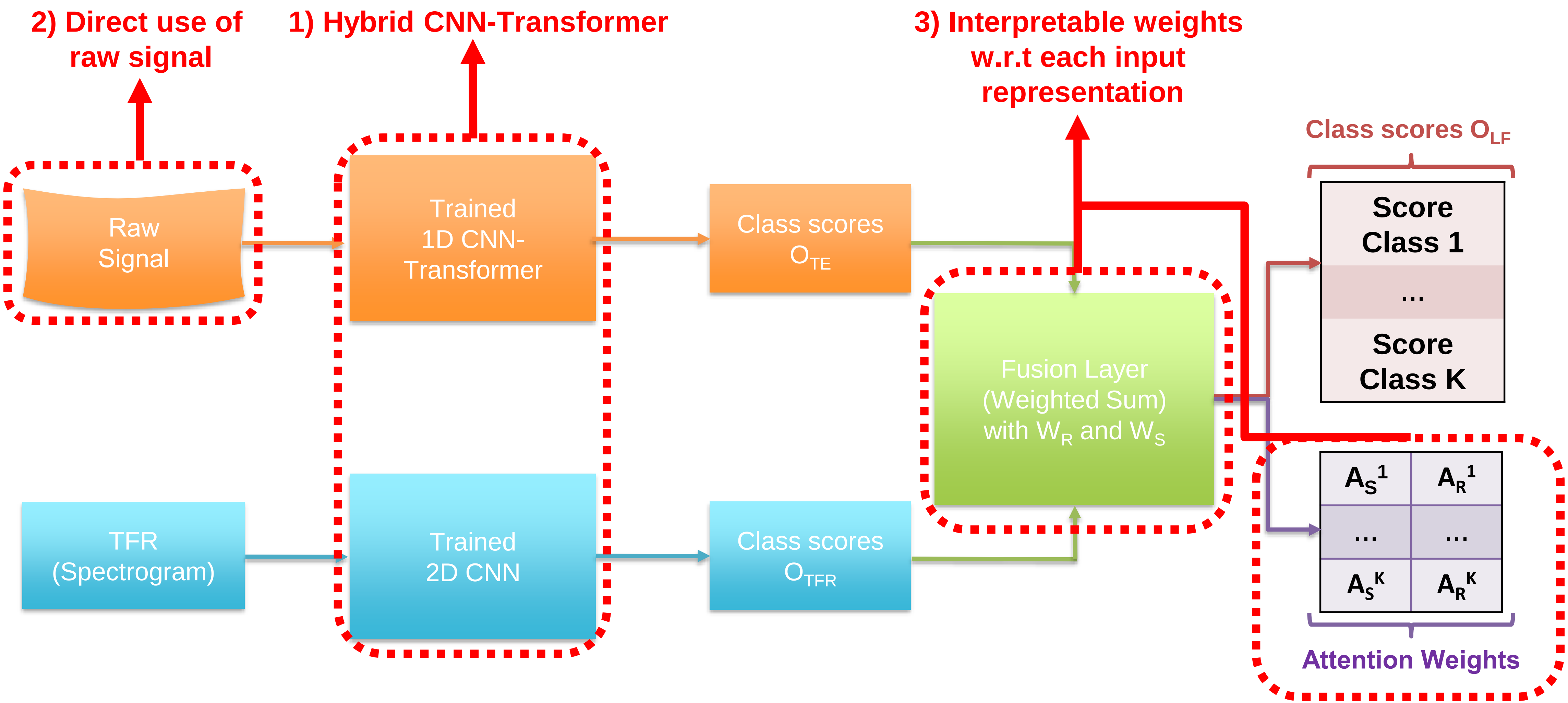


Figure - Proposed hybrid CNN Transformer global model

Guided and regularized intermediate fusion

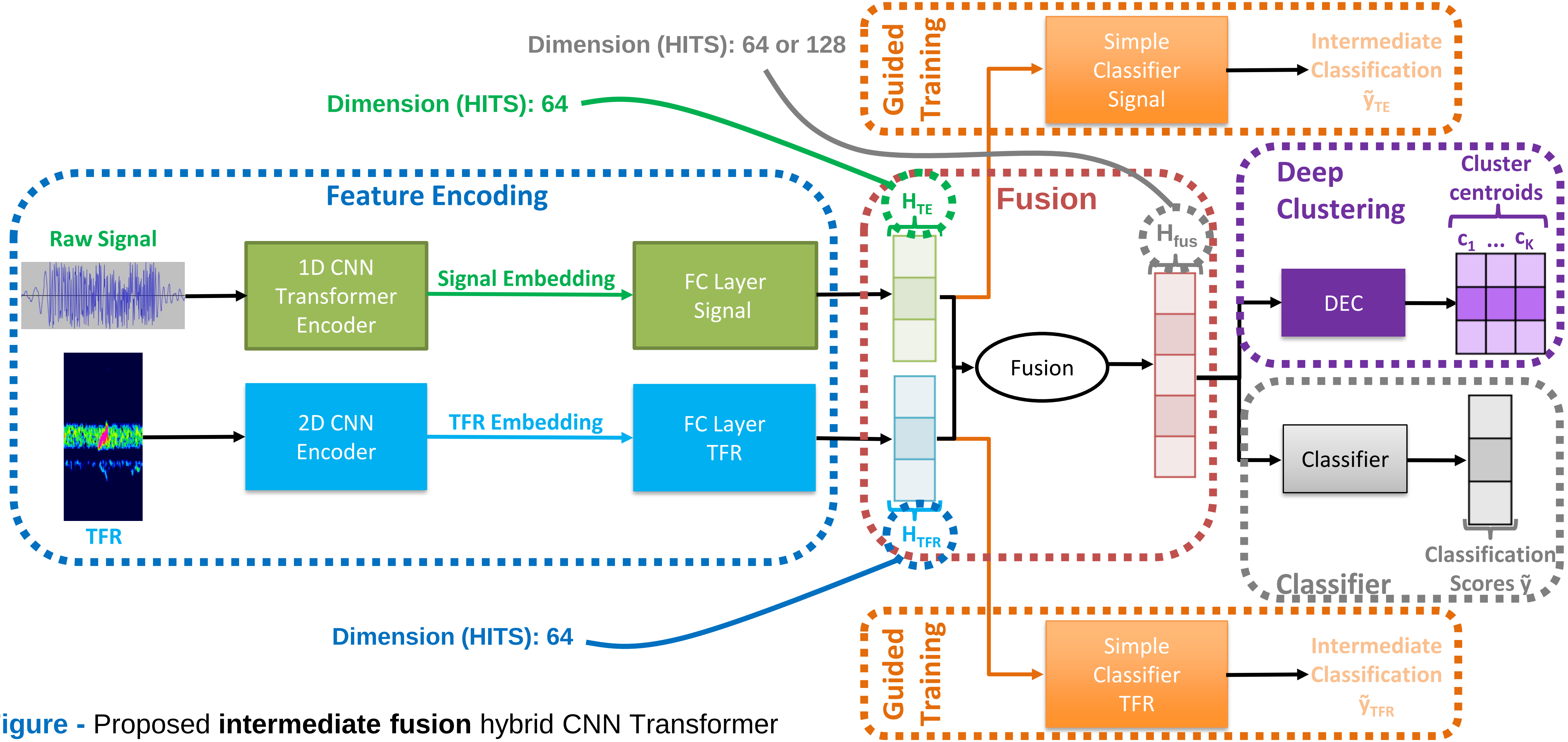


Figure - Proposed **intermediate fusion** hybrid CNN Transformer model.

Results: SOTA comparison HITS validation

Single feature models

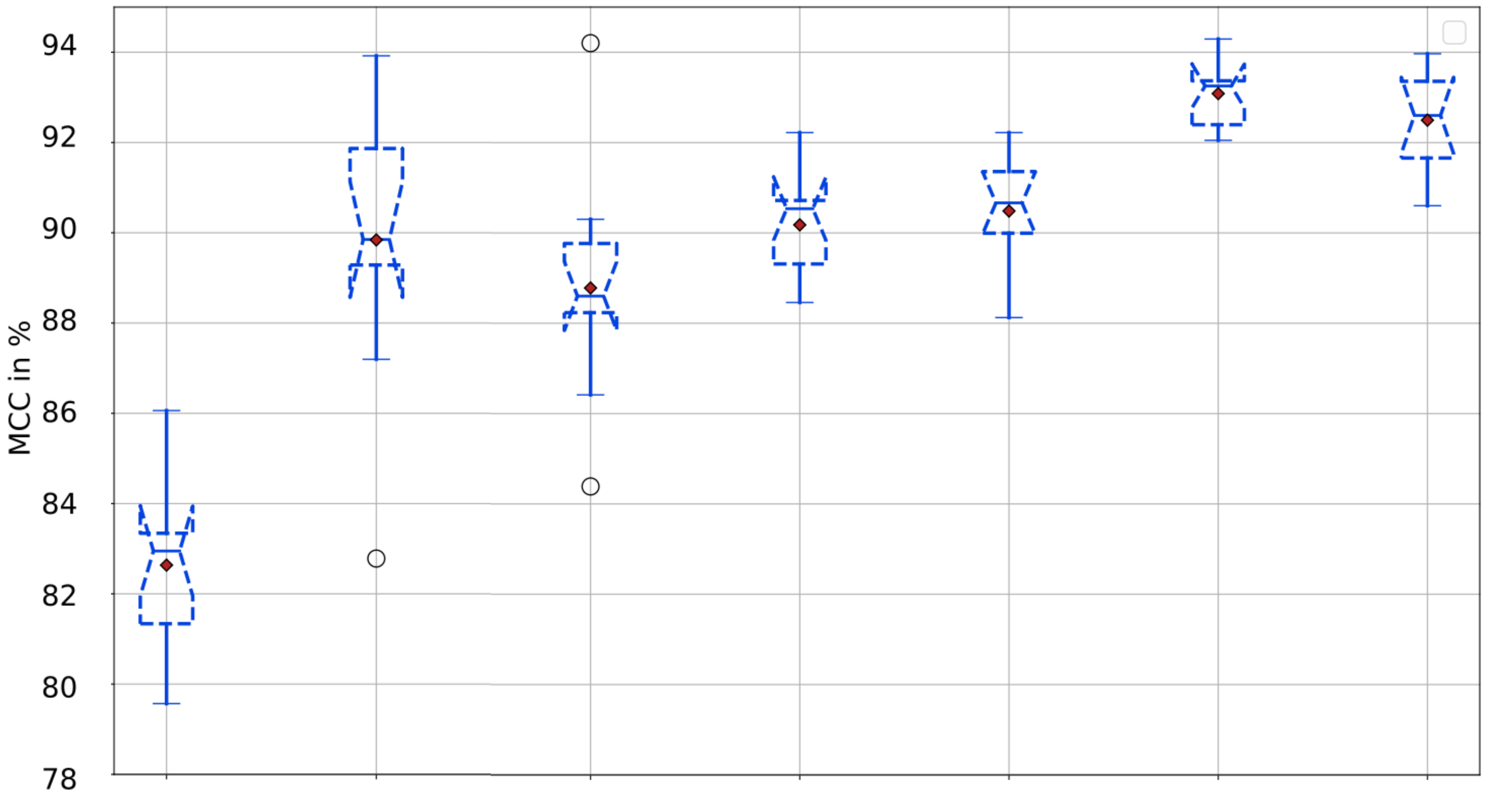
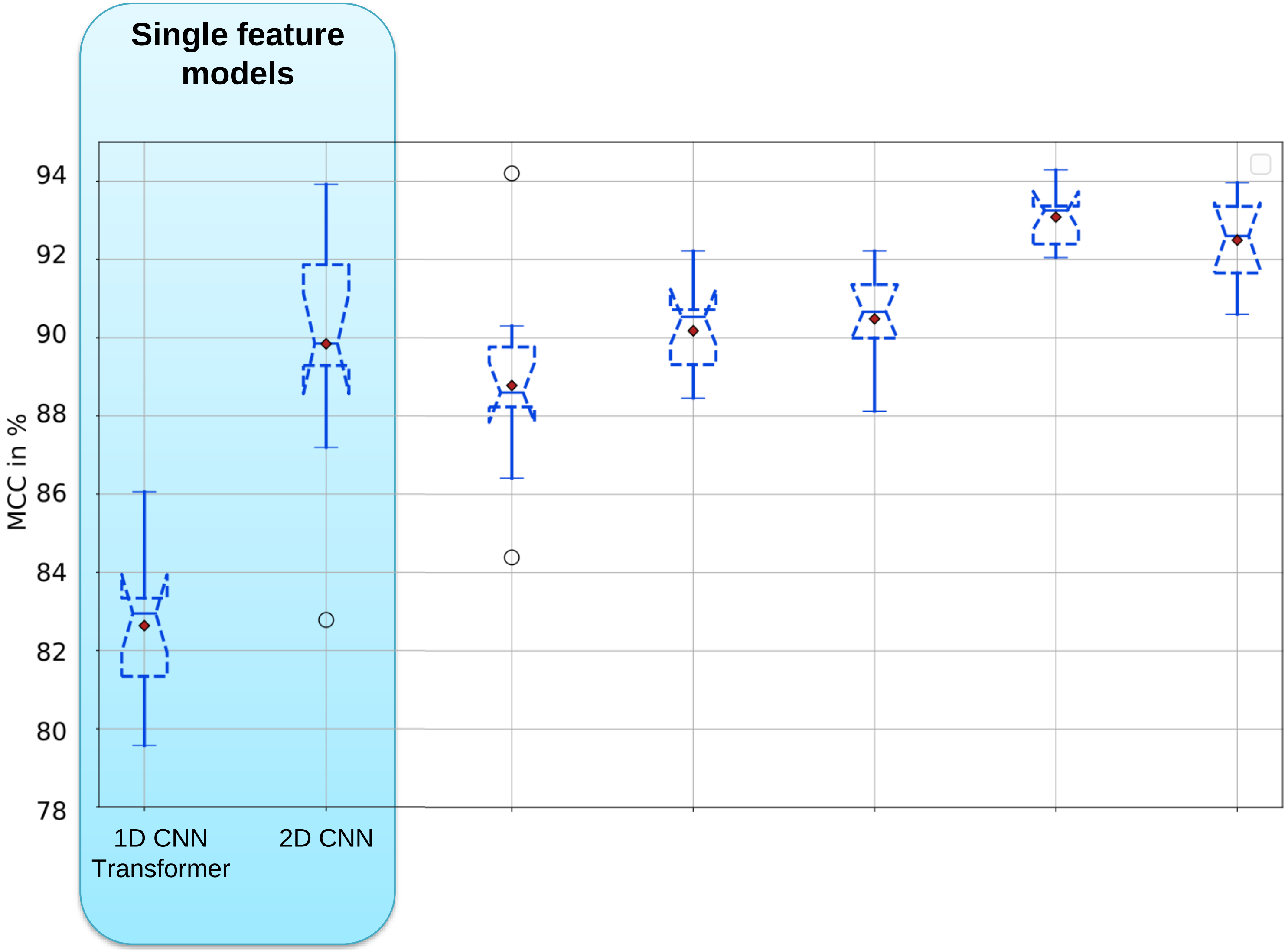


Figure - Comparison of the classification performances of different single and multi-feature models on the HITS dataset

Results: SOTA comparison HITS validation



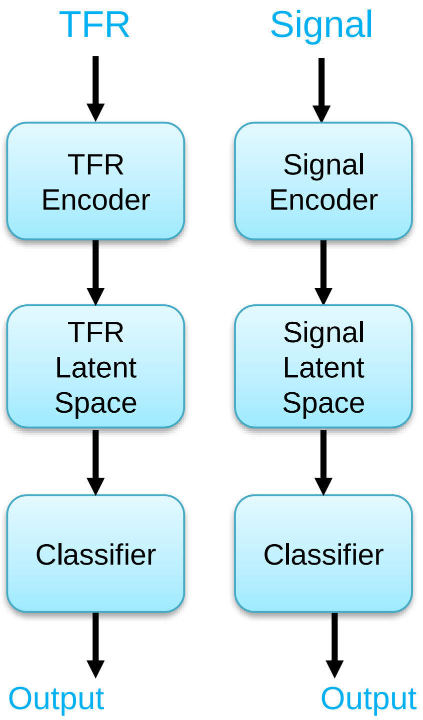


Figure - Comparison of the classification performances of different single and multi-feature models on the HITS dataset

Results: SOTA comparison HITS validation

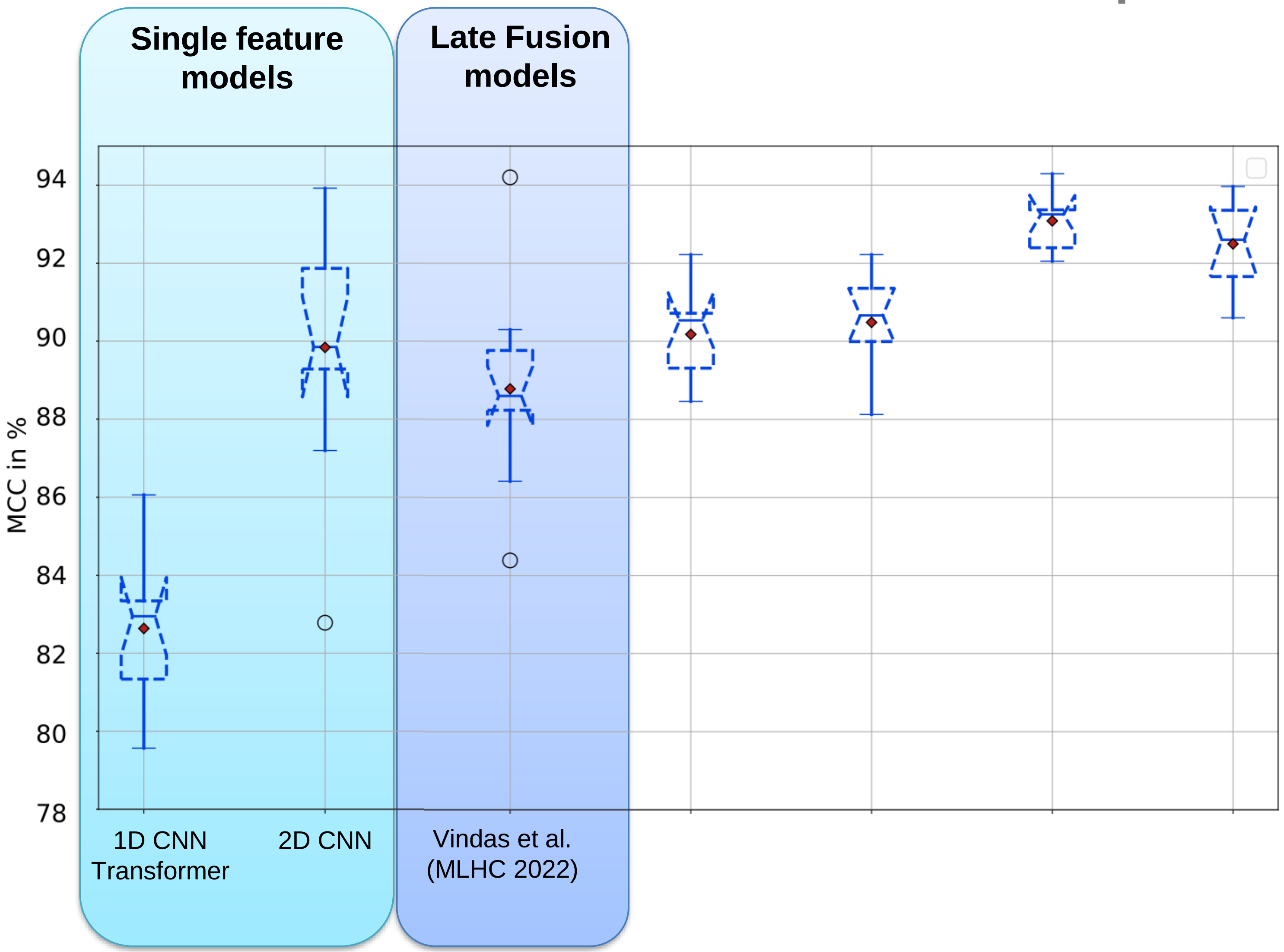
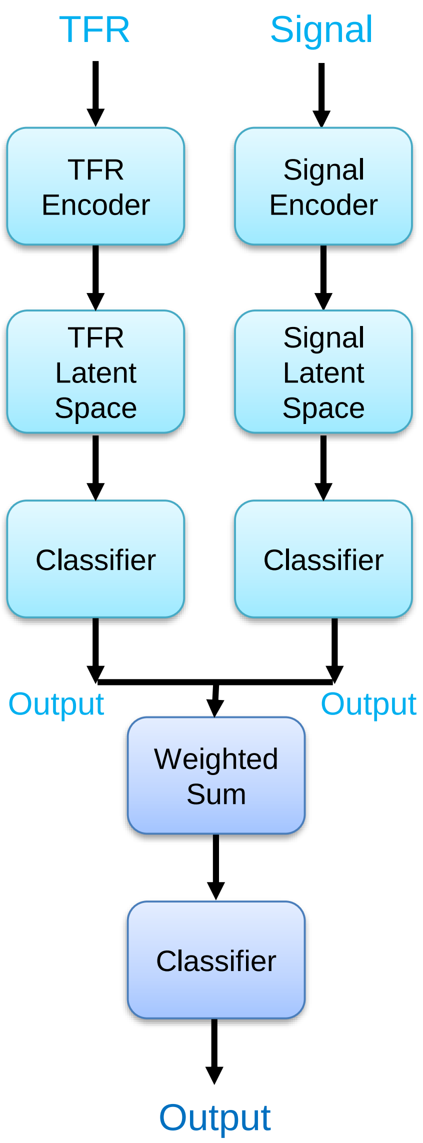
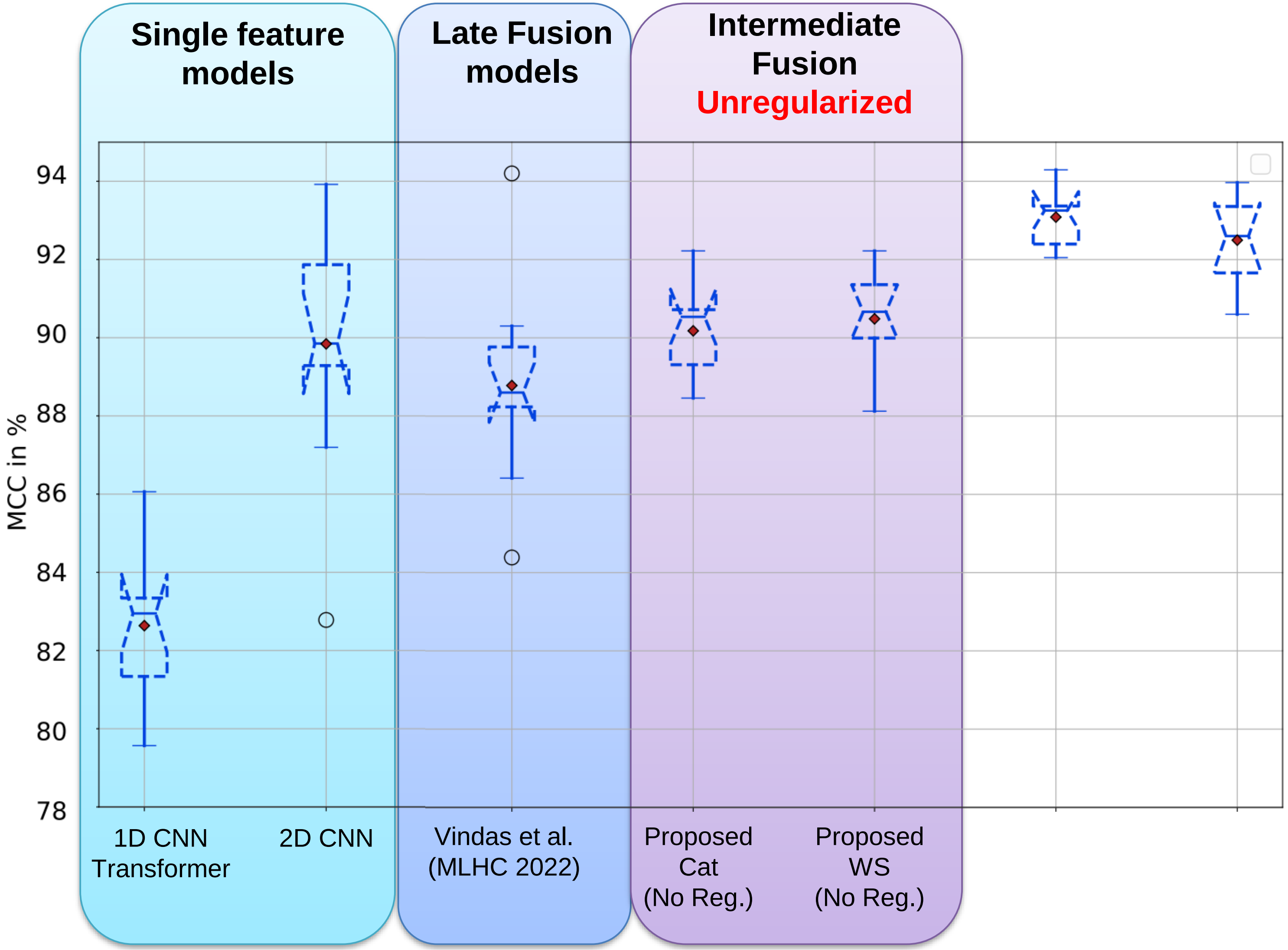
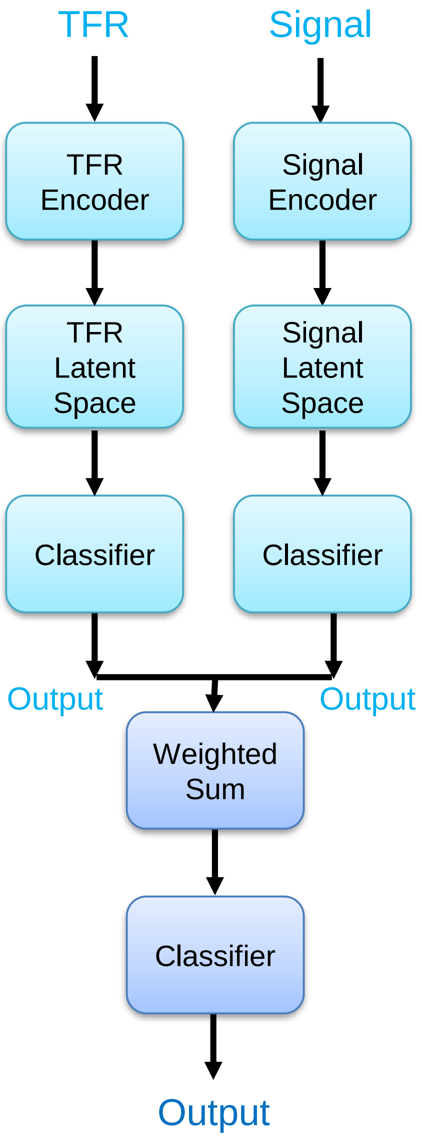


Figure - Comparison of the classification performances of different single and multi-feature models on the HITS dataset



Results: SOTA comparison HITS validation





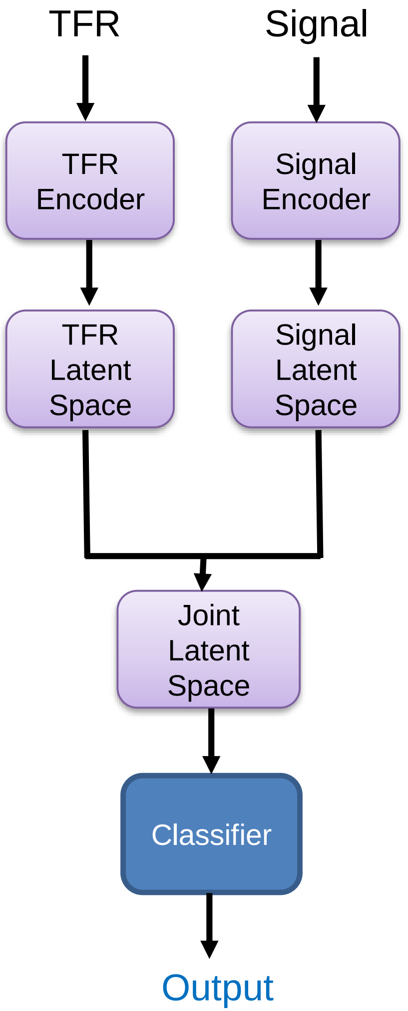
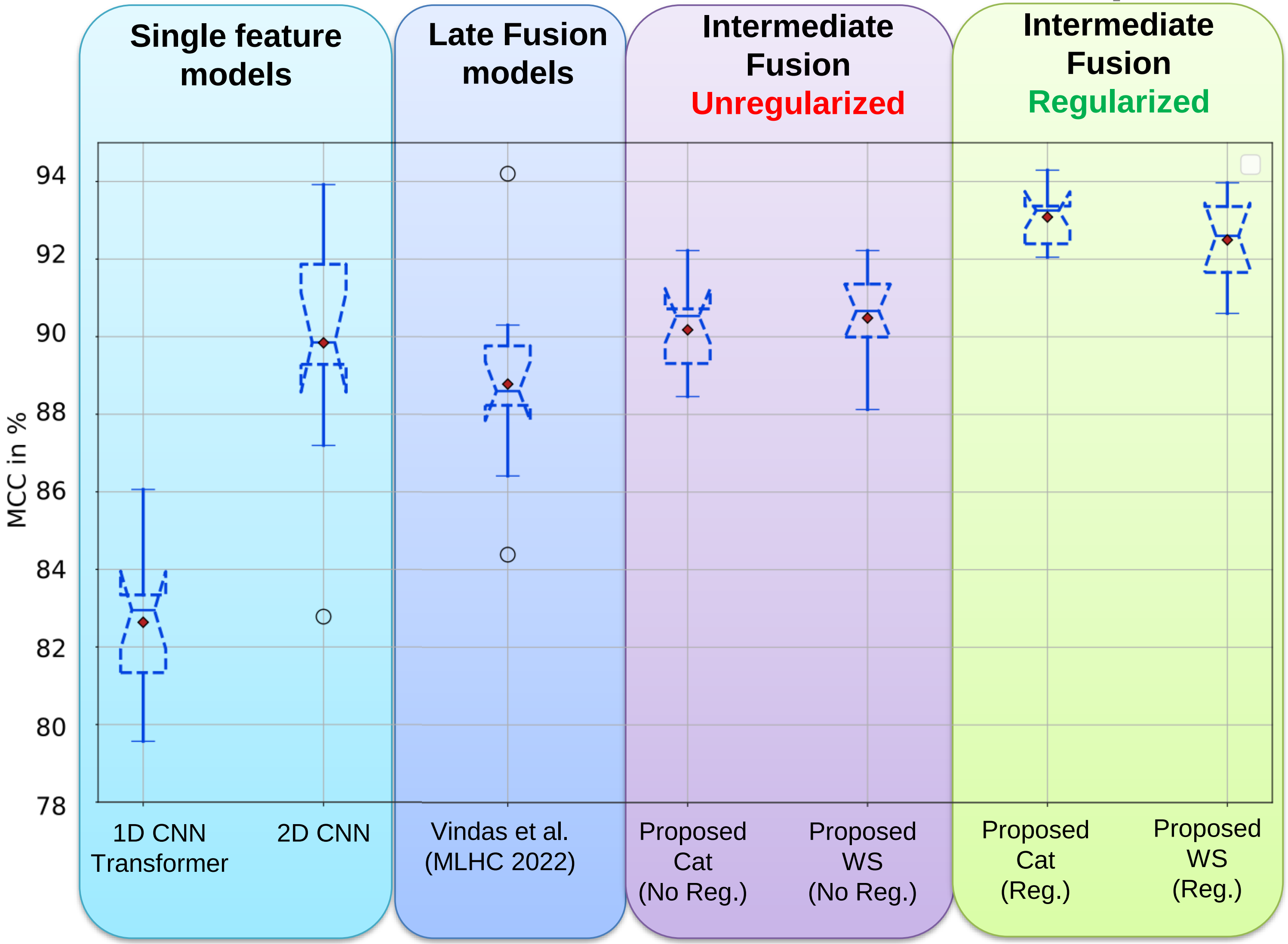
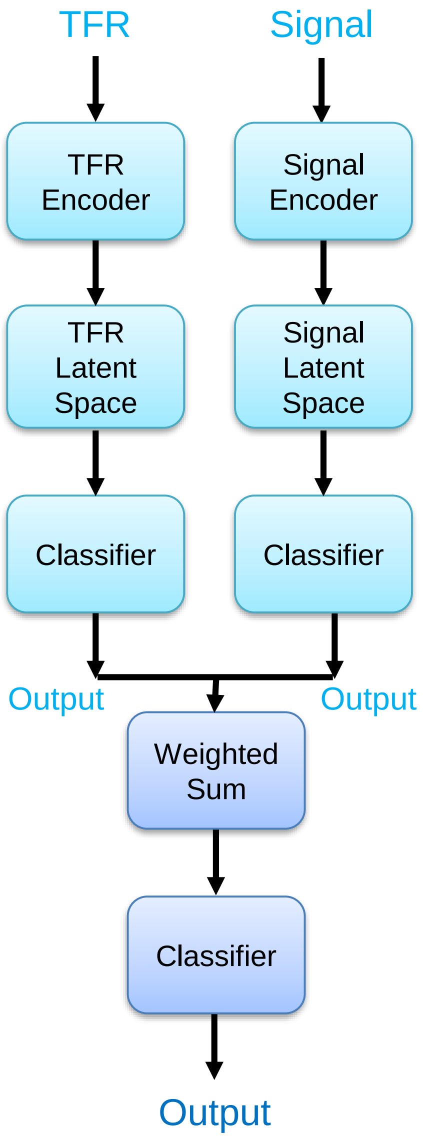


Figure - Comparison of the classification performances of different single and multi-feature models on the HITS dataset

Results: SOTA comparison HITS validation





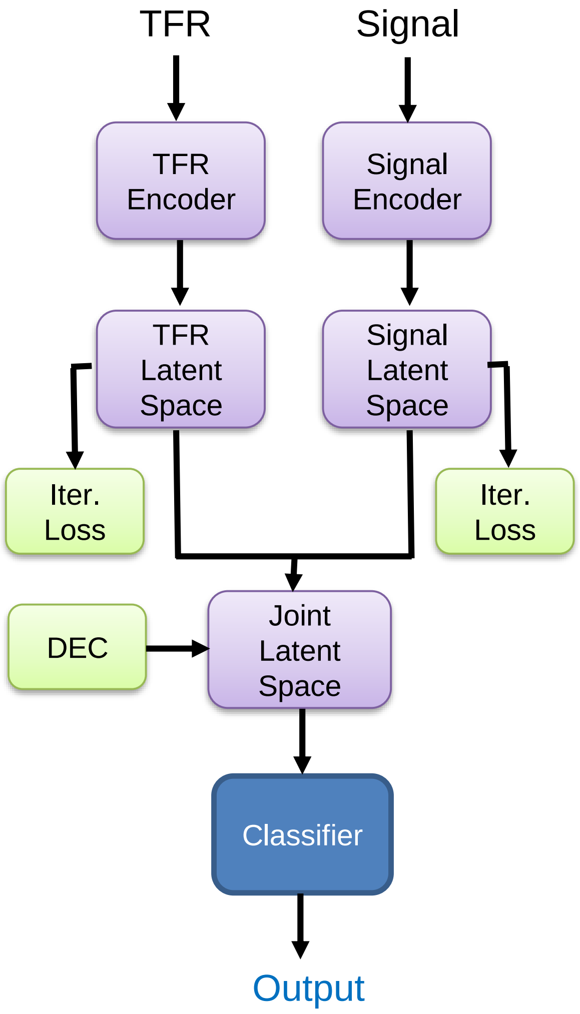


Figure - Comparison of the classification performances of different single and multi-feature models on the HITS dataset

Results Multi-feature classification

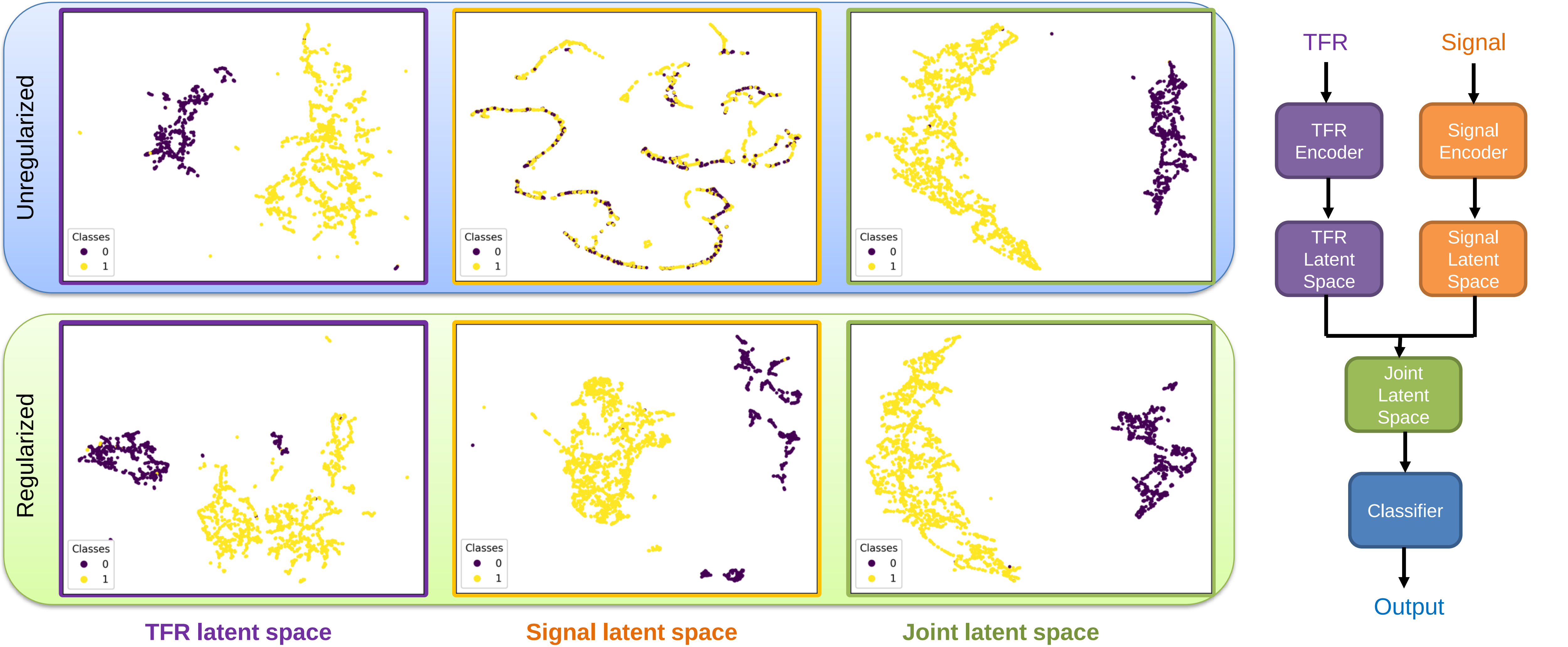
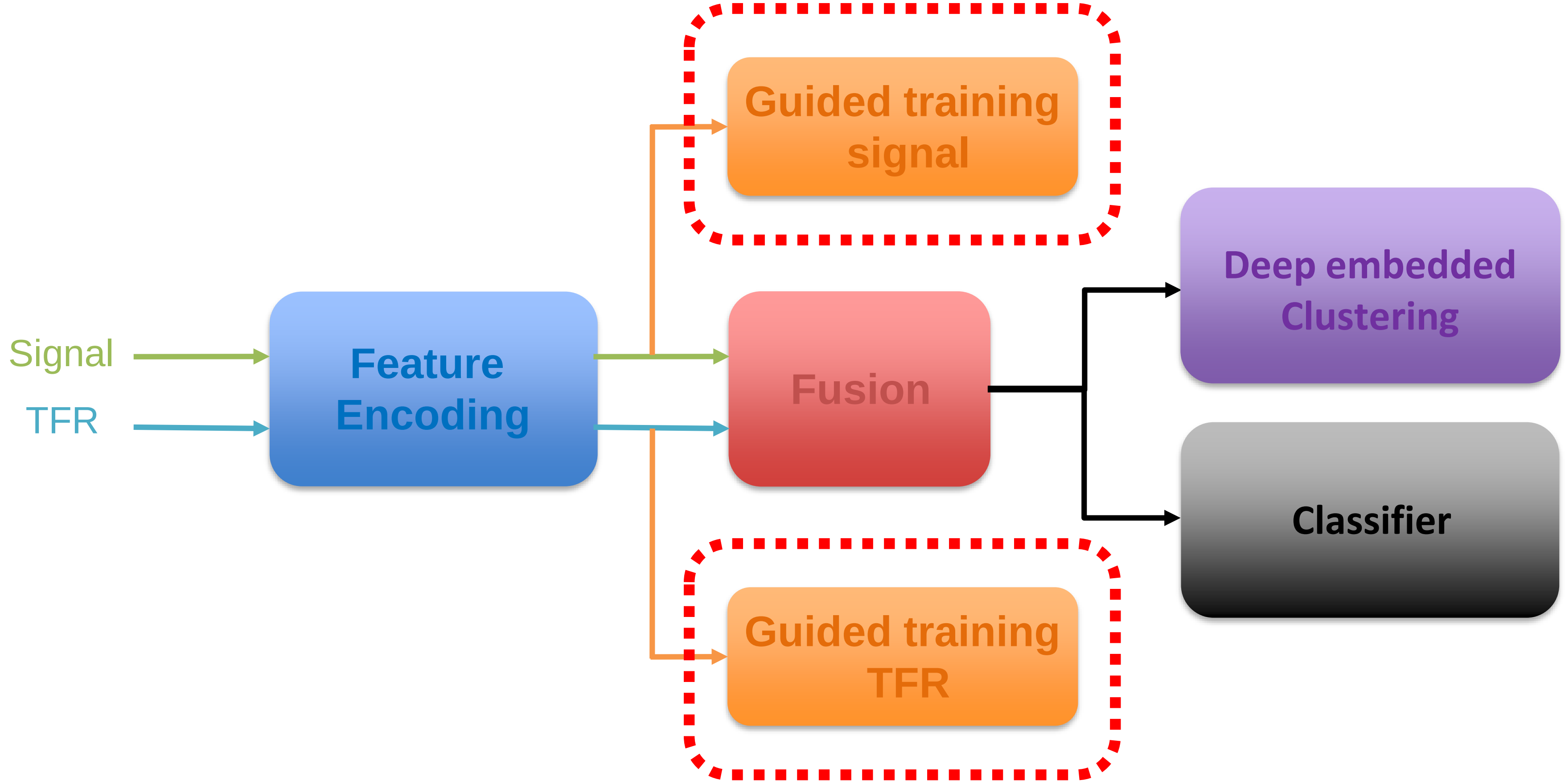


FIGURE - UMAP projections of the different latent spaces of the multi-feature intermediate fusion classification model on the PTB dataset

GDEC


Signal
TFR
Feature Encoding
Guided training signal
Fusion
Guided training TFR
Deep embedded Clustering
Classifier

Experiment: influence guided training

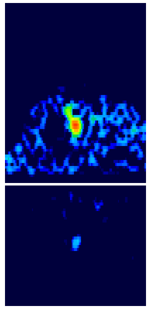
Objective:

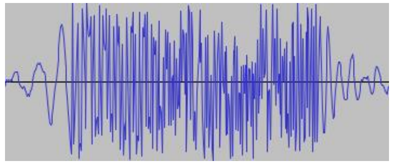
- Influence signal guided training.
- Influence TFR guided training.

Datasets:

HITS:

- TCD Data.
- 1545 samples.
- Three classes.
- Sampling frequency: 4385 Hz.





Metrics:

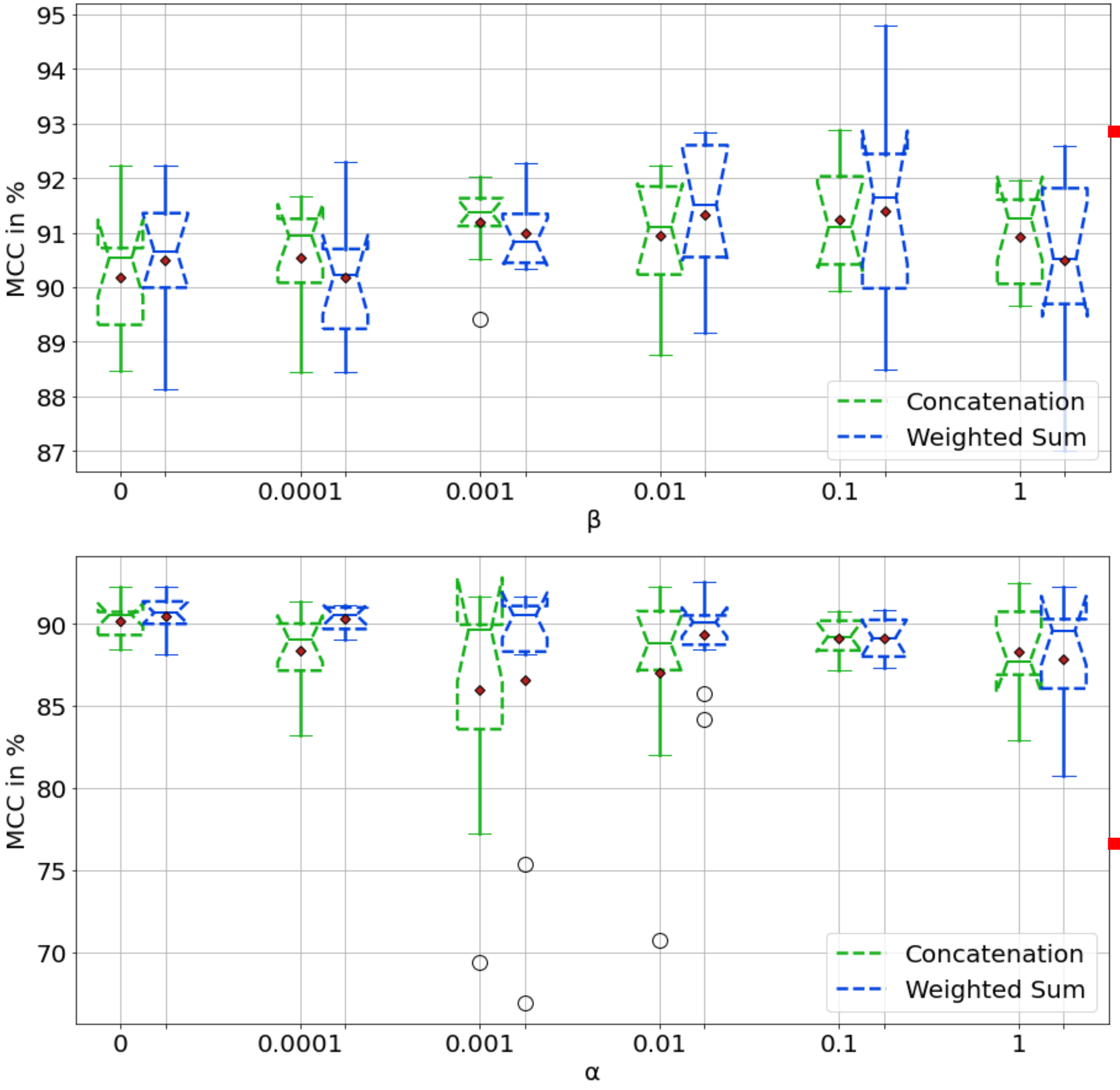
- Mathews Correlation Coefficient (MCC).

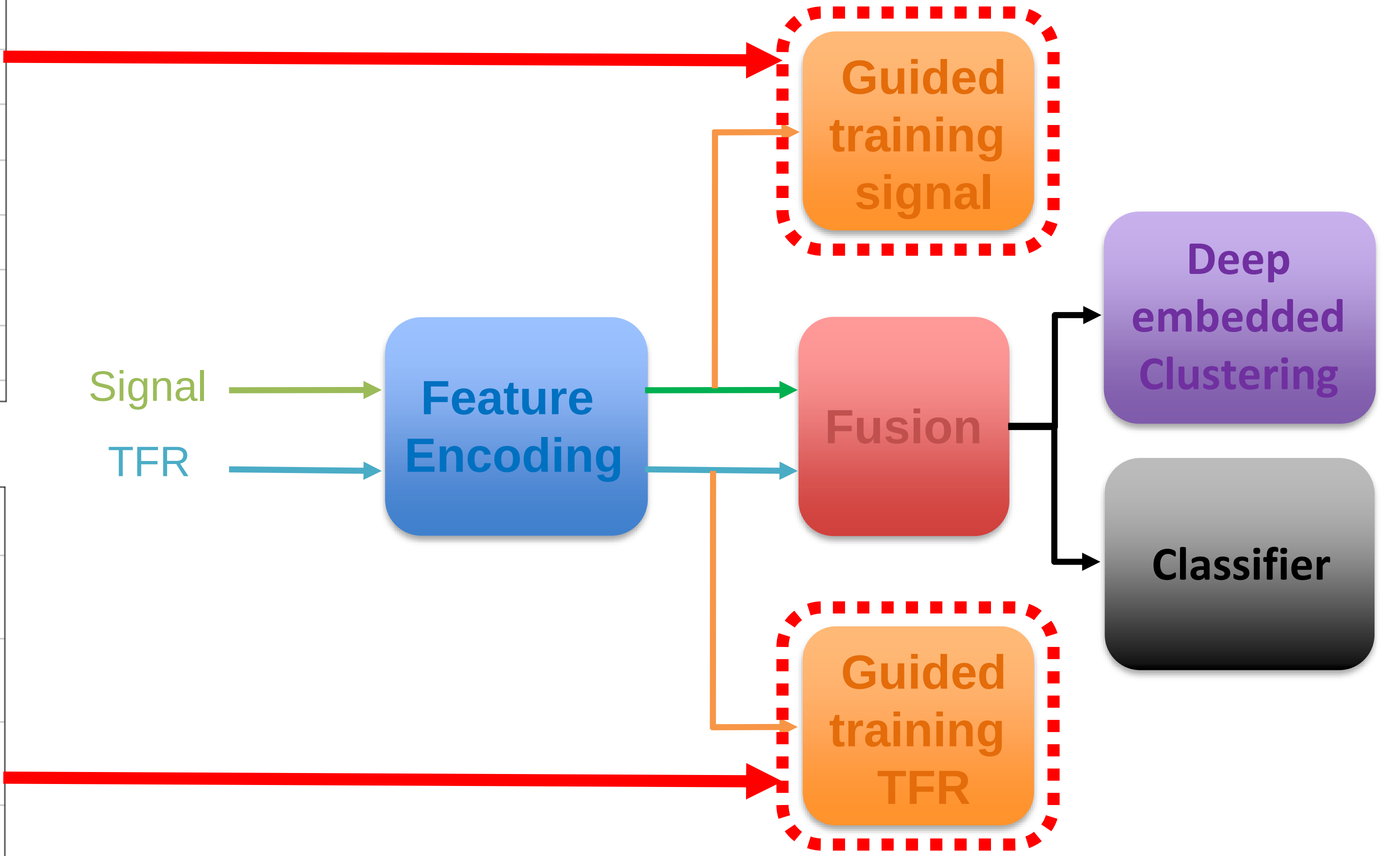
Loss function:

- Cross entropy (CE)

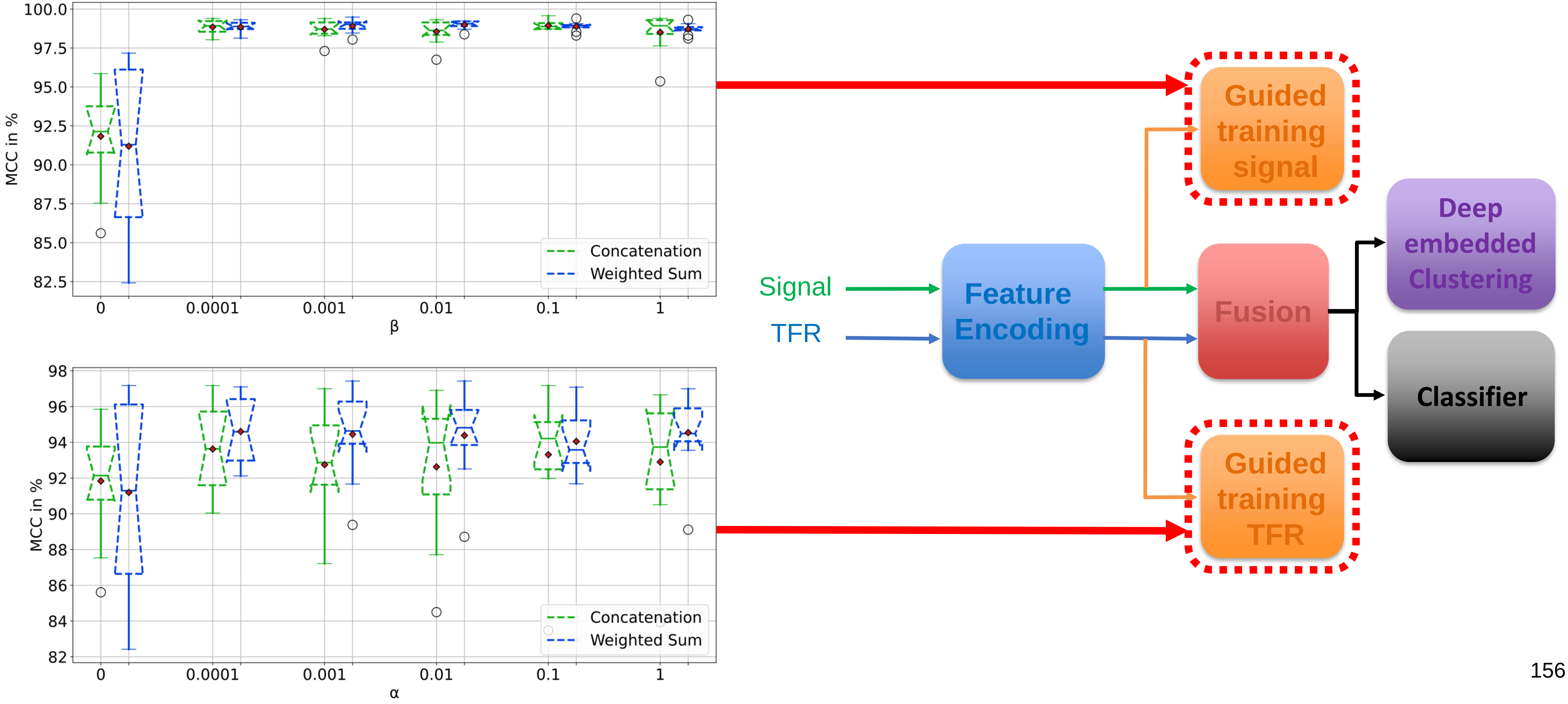
Class	Number of samples
Artifact	403
Gaseous Emboli	569
Solid Emboli	569
Unknown	4

Results

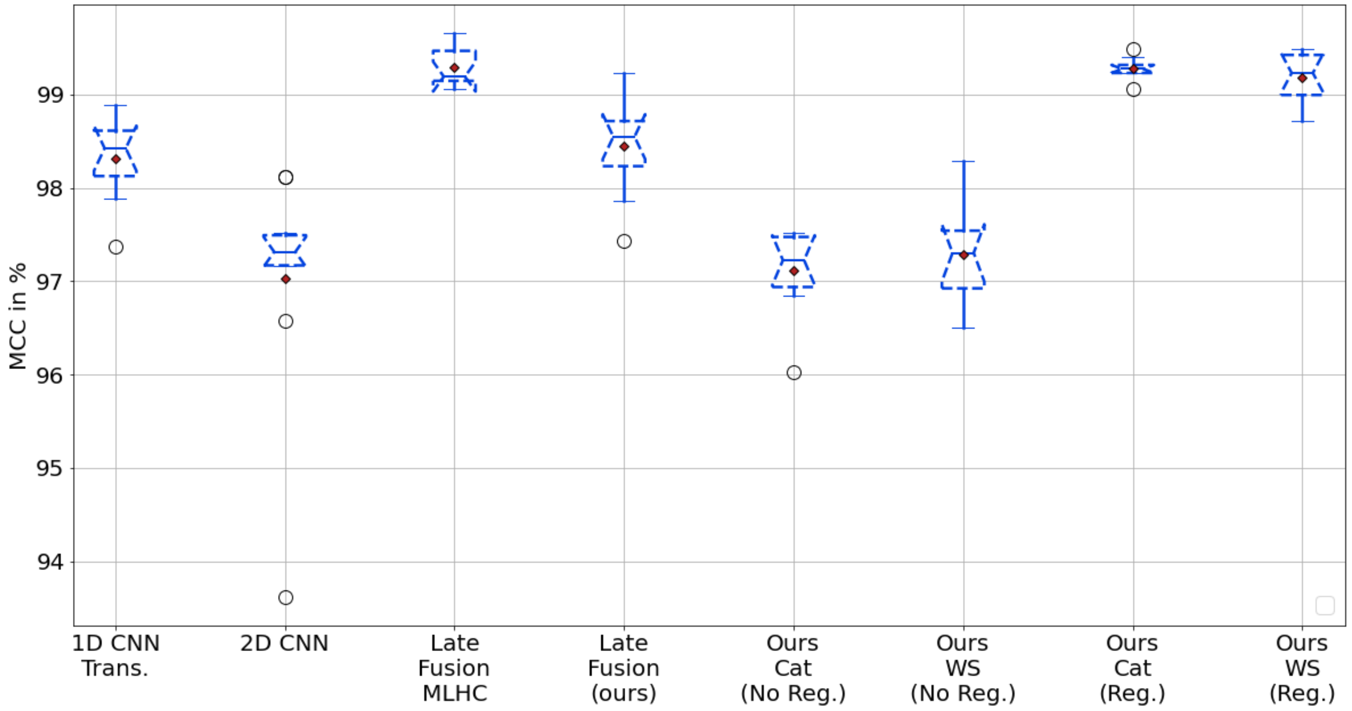

95
94
93
92
91
90
89
88
87
MCC in %
0
0.0001
0.001
0.01
0.1
1
β
Concatenation
Weighted Sum
90
85
80
75
70
MCC in %
α


Signal
TFR
Feature Encoding
Guided training signal
Fusion
Guided training TFR
Deep embedded Clustering
Classifier

Results: influence guiding PTB



Results Multi-feature classification in PTB



Model	Features	Fusion	F1 Score
1D CNN-Trans.	Raw Signal	-	99.16 ± 0.22
2D CNN	TFR	-	98.51 ± 0.61
Ahmad et al. (2021)	GAF MTF RP		98
Late Fusion (MLHC)		Weight. Sum	99.65 ± 0.10
Late Fusion (ours)			99.22 ± 0.25
Ours (No Reg.)		Cat.	98.60 ± 0.22
Ours (No Reg.)	**Both**	Weight. Sum	98.64 ± 0.25
Ours (Reg.)		**Cat.**	**99.64 ± 0.05**
Ours (Reg.)		Weight. Sum	99.59 ± 0.13

FIGURE - Comparison of the classification performances of different single and multi-feature models on the PTB dataset

Late fusion weights interpretability

Late fusion weights interpretability

Attention weights for the HITS dataset

Late fusion weights interpretability

Class	Spectrogram	Raw Signal
Artifacts	0.46 ± 0.29	0.54 ± 0.29
Gaseous Emboli	0.65 ± 0.17	0.35 ± 0.17
Solid Emboli	0.71 ± 0.15	0.29 ± 0.15

Attention weights for the HITS dataset

Late fusion weights interpretability

Class	Spectrogram	Raw Signal
Artifacts	0.46 ± 0.29	0.54 ± 0.29
Gaseous Emboli	0.65 ± 0.17	0.35 ± 0.17
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Attention weights for the HITS dataset

Attention weights for the PTB dataset

Late fusion weights interpretability

Class	Spectrogram	Raw Signal
Artifacts	0.46 ± 0.29	0.54 ± 0.29
Gaseous Emboli	0.65 ± 0.17	0.35 ± 0.17
Solid Emboli	0.71 ± 0.15	0.29 ± 0.15

Attention weights for the HITS dataset

Class	Spectrogram	Raw Signal
Normal	0.49 ± 0.12	0.51 ± 0.12
Abnormal	0.18 ± 0.10	0.82 ± 0.10

Attention weights for the PTB dataset

Late fusion weights interpretability

Class	Spectrogram	Raw Signal
Artifacts	0.46 ± 0.29	0.54 ± 0.29
Gaseous Emboli	0.65 ± 0.17	0.35 ± 0.17
Solid Emboli	0.71 ± 0.15	0.29 ± 0.15

Attention weights for the HITS dataset

Class	Spectrogram	Raw Signal
Normal	0.49 ± 0.12	0.51 ± 0.12
Abnormal	0.18 ± 0.10	0.82 ± 0.10

Attention weights for the PTB dataset

Attention weights for the MIT-BIH dataset

Late fusion weights interpretability

Class	Spectrogram	Raw Signal
Artifacts	0.46 ± 0.29	0.54 ± 0.29
Gaseous Emboli	0.65 ± 0.17	0.35 ± 0.17
Solid Emboli	0.71 ± 0.15	0.29 ± 0.15

Attention weights for the HITS dataset

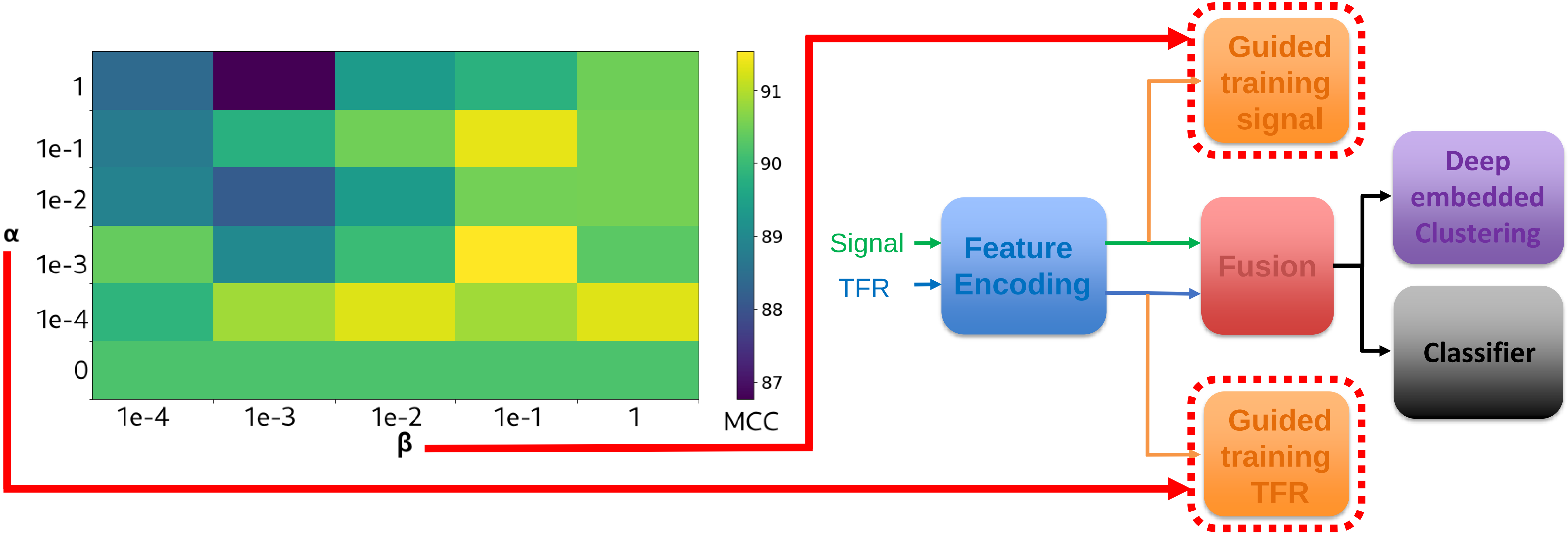
Class	Spectrogram	Raw Signal
Normal	0.49 ± 0.12	0.51 ± 0.12
Abnormal	0.18 ± 0.10	0.82 ± 0.10

Attention weights for the PTB dataset

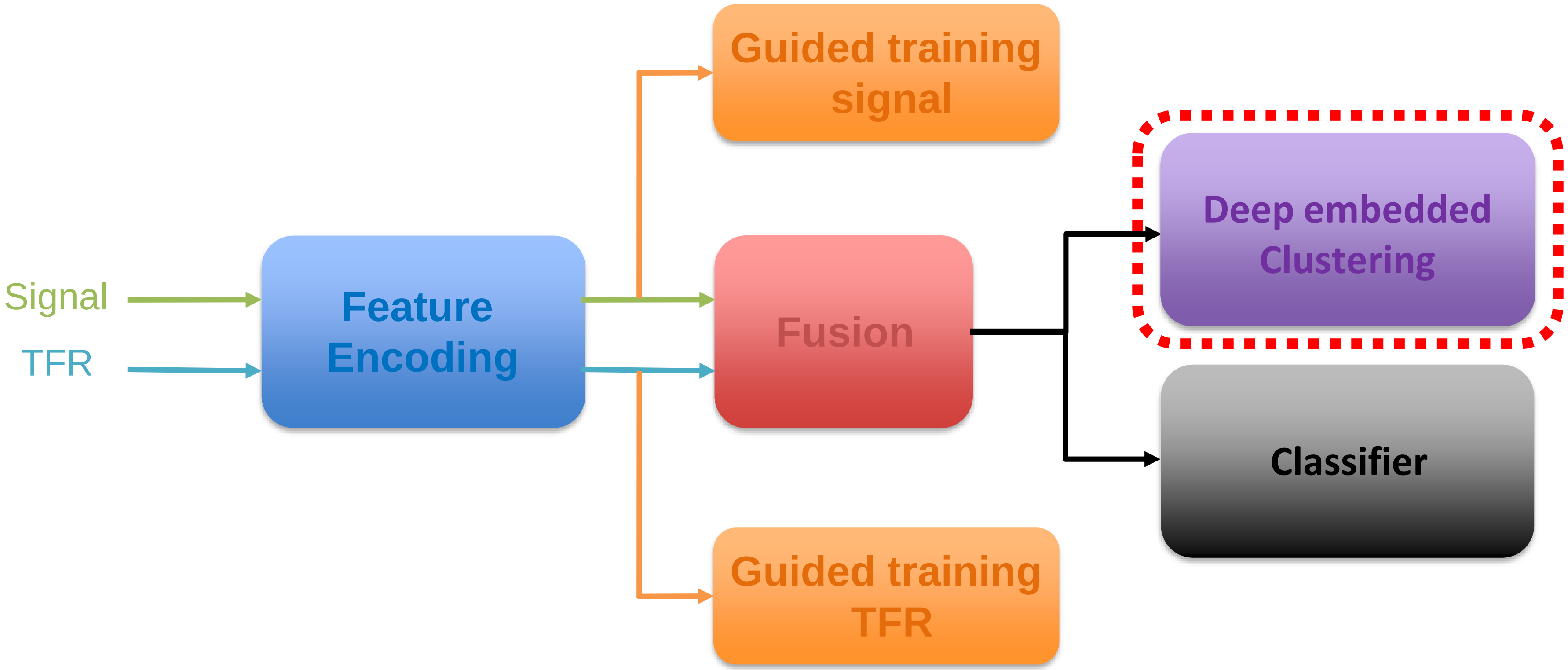
Class	Spectrogram	Raw Signal
N	0.48 ± 0.01	0.52 ± 0.01
S	0.50 ± 0.01	0.50 ± 0.01
V	0.50 ± 0.01	0.50 ± 0.01
F	0.49 ± 0.02	0.51 ± 0.02
Q	0.50 ± 0.003	0.50 ± 0.003

Attention weights for the MIT-BIH dataset

Results: influence guiding HITS bot



GDEC


Signal
TFR
Feature Encoding
Guided training signal
Fusion
Guided training TFR
Deep embedded Clustering
Classifier

Experiment: influence DEC

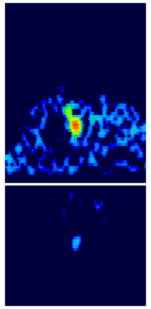
Objective:

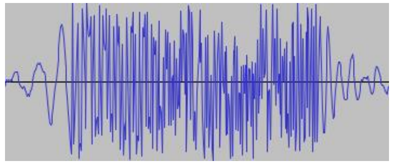
- Influence DEC on the classification performance.

Datasets:

HITS:

- TCD Data.
- 1545 samples.
- Three classes.
- Sampling frequency: 4385 Hz.





Metrics:

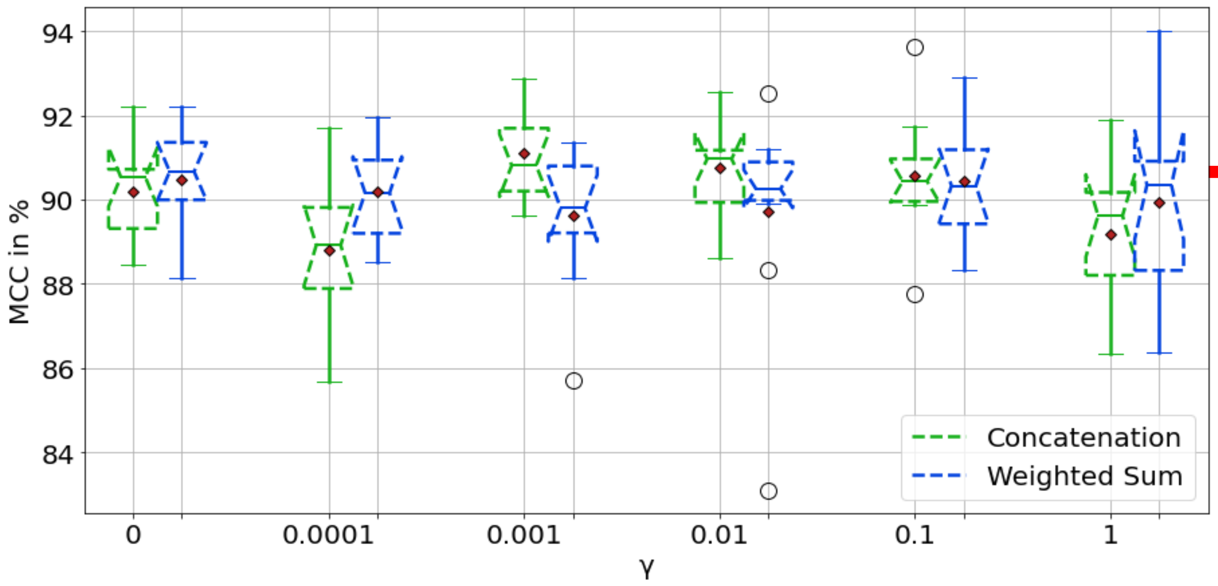
- Mathews Correlation Coefficient (MCC).

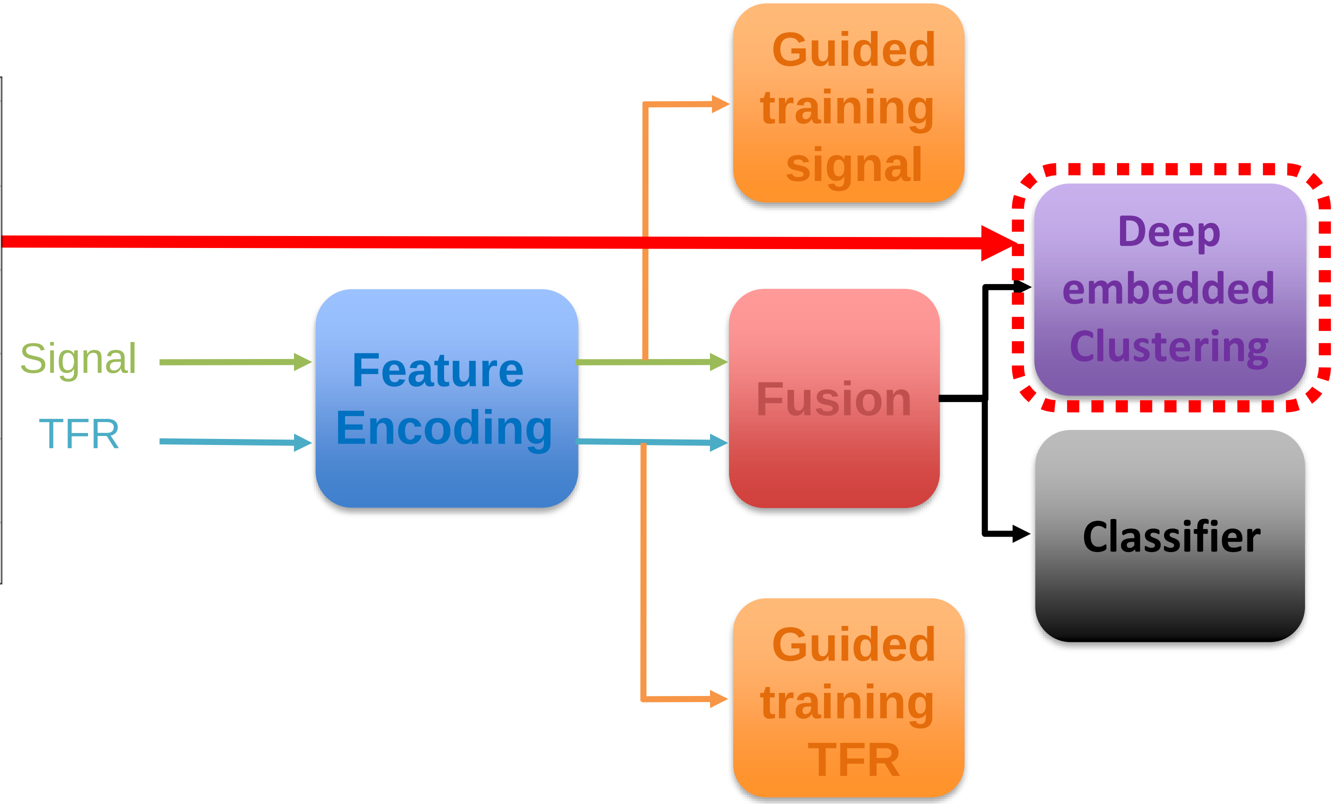
Loss function:

- Cross entropy (CE)

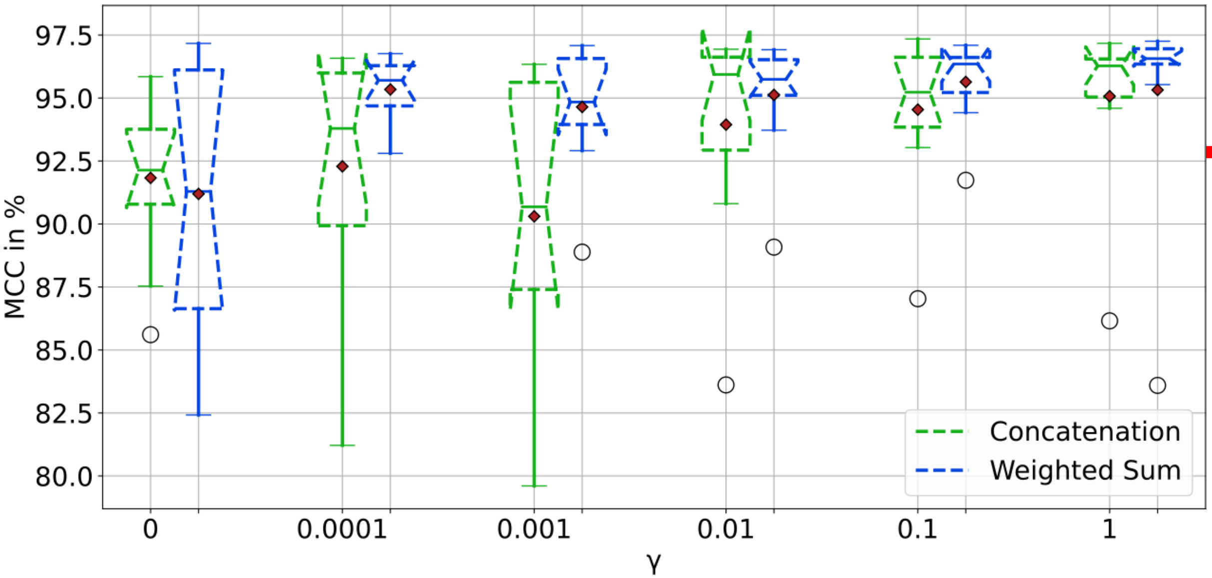
Class	Number of samples
Artifact	403
Gaseous Emboli	569
Solid Emboli	569
Unknown	4

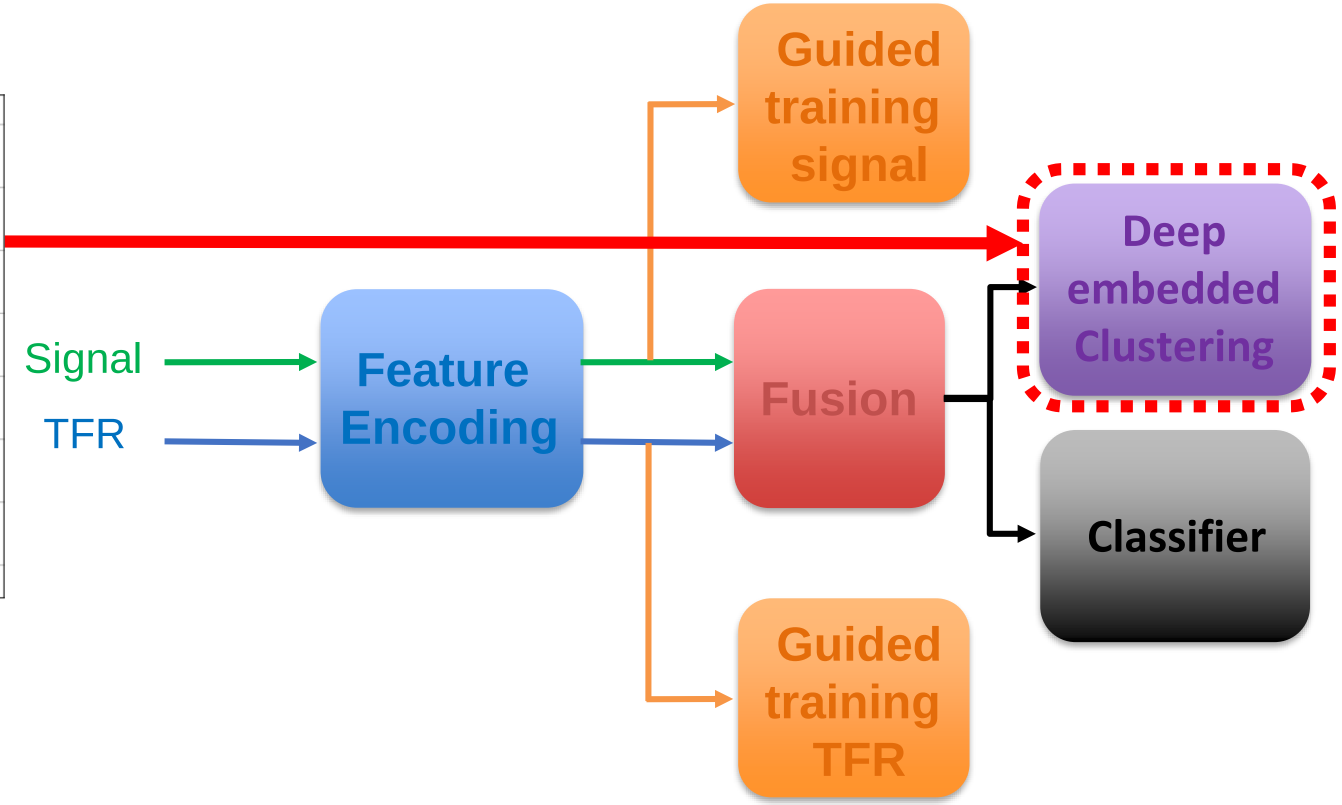
Results


MCC in %
94
92
90
88
86
84
0
0.0001
0.001
0.01
0.1
1
γ
Concatenation
Weighted Sum

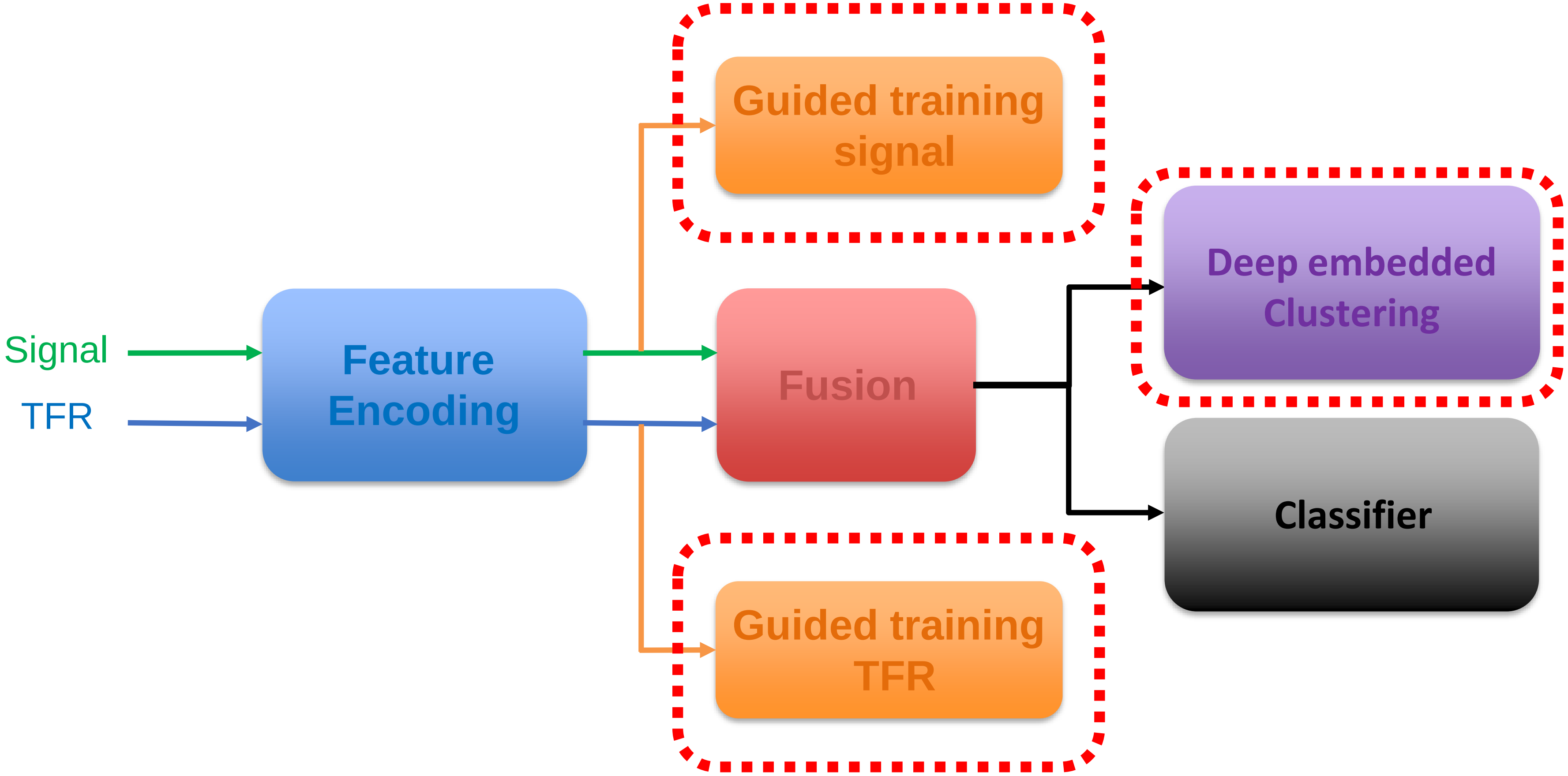

Signal
TFR
Feature Encoding
Guided training signal
Fusion
Guided training TFR
Deep embedded Clustering
Classifier

Results: influence DEC PTB





GDEC


Signal
TFR
Feature Encoding
Guided training signal
Fusion
Guided training TFR
Deep embedded Clustering
Classifier

Experiment: noise tolerance on HITS-sada

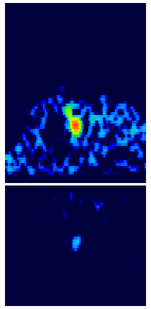
Objective:

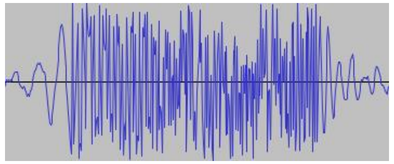
- Study the robustness of GDEC to noisy labeled datasets.

Datasets:

HITS-sada:

- TCD **semi-automatically labeled** data.
- 8 685 samples.
- Three classes.
- Sampling frequency: 4385 Hz.





Metrics:

- Mathews Correlation Coefficient (MCC).
- F1-Score.
- Number of parameters.
- Number of mult-adds.

Loss function:

- **Generalized Cross entropy (GCE).**

Class	Number of samples
Artifact	6 987
Gaseous Emboli	1 002
Solid Emboli	696

Results

Model	MCC	F1-Score	Accuracy	No. Parameters	No. mult-adds (G)
2D CNN	84.03 ± 1.20	86.81 ± 1.50	90.68 ± 1.12	1 681 923	1.23
1D CNN-trans.	85.74 ± 1.16	88.96 ± 0.78	91.35 ± 0.77	**766 271**	**0.173**
MIF-GR	**87.35 ± 0.85**	**89.41 ± 0.64**	**92.59 ± 0.50**	4 833 727	1.40

Table – Multi-feature GDCE compared to single feature models on a noisy semi-automatically labeled dataset HITS-sada.

Robustness DEC Imbalanced Datasets

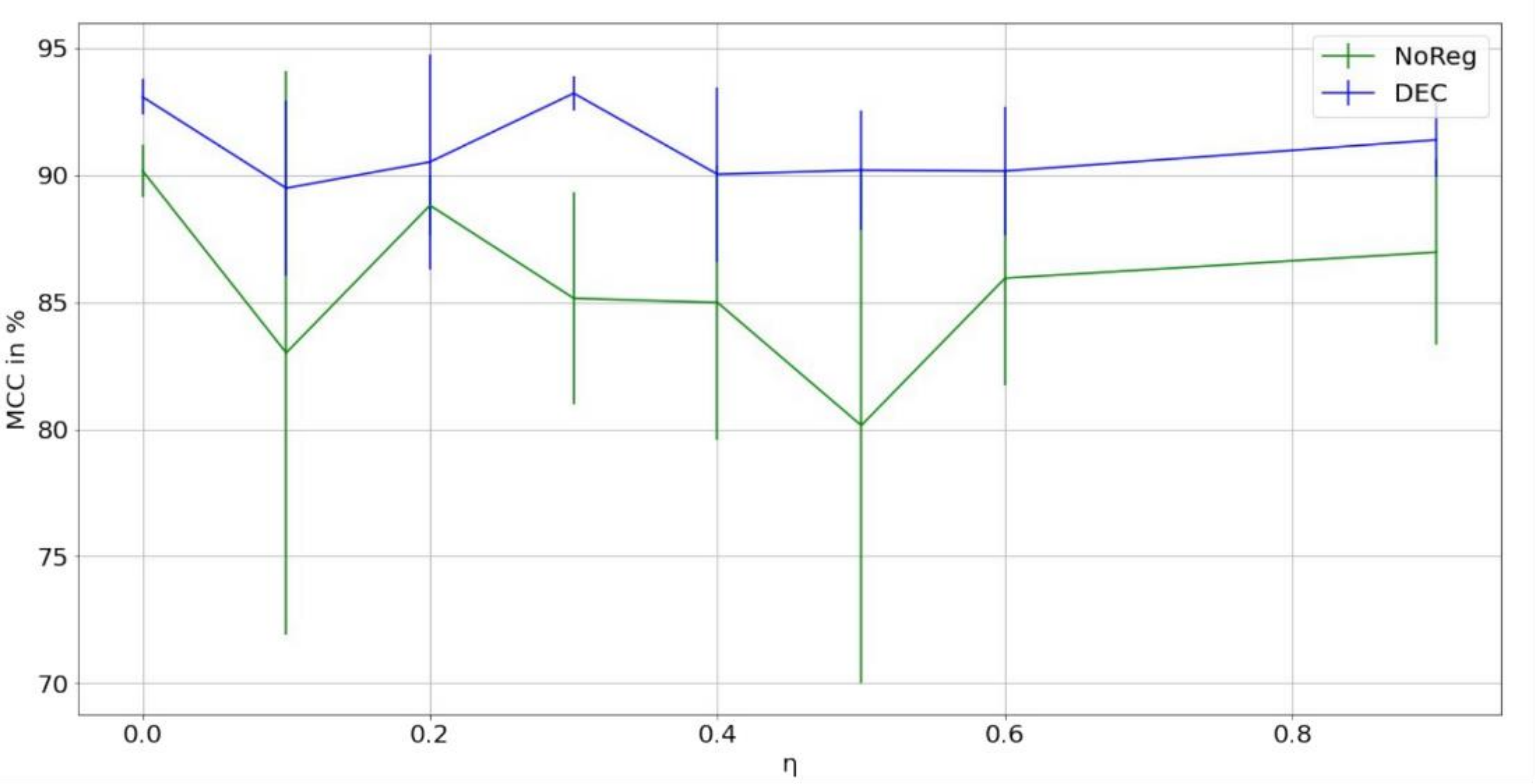


FIGURE - MCC of the multi-feature classification model on the HITS dataset for different levels of label noise.

Robustness DEC Imbalanced Datasets

Noise Rate	Clean Samples	GDEC	Loss	MCC
5	Yes	No	CE	97.08 ± 0.53
		Yes		99.32 ± 0.17
	No	No		88.61 ± 0.74
		Yes		93.13 ± 0.31
	Yes	No	GCE	96.58 ± 0.49
		Yes		98.37 ± 0.27
	No	No		94.10 ± 1.09
		Yes		96.70 ± 0.54

Noise rate of 5 %

Noise Rate	Clean Samples	GDEC	Loss	MCC
10	Yes	No	CE	96.98 ± 0.35
		Yes		99.30 ± 0.19
	No	No		78.55 ± 1.45
		Yes		82.30 ± 1.15
	Yes	No	GCE	96.27 ± 0.59
		Yes		98.57 ± 0.36
	No	No		90.22 ± 1.30
		Yes		91.90 ± 1.18

Noise rate of 10 %

Noise Rate	Clean Samples	GDEC	Loss	MCC
20	Yes	No	CE	96.96 ± 0.54
		Yes		98.99 ± 0.27
	No	No		59.98 ± 1.98
		Yes		63.77 ± 2.08
	Yes	No	GCE	95.66 ± 0.70
		Yes		97.84 ± 0.52
	No	No		71.63 ± 2.52
		Yes		71.66 ± 3.48

Noise rate of 20 %

Table - MCC of the multi-feature classification model on the PTB dataset for different levels of label noise.

Model compression

Model	SA Finished	MCC	Drop MCC	Sparsity rate (%)	Tuning duration
Full precision	-	95.85 ± 0.69	-	0 ± 0	-
TTQ	-	93.86 ± 0.92		29.98 ± 1.42	200
Proposed	-	93.80 ± 0.26		77.41 ± 2.09	200
Proposed SA (x in [-1, 0], y in [0, 1])	No	94.51 ± 0.77		60.96 ± 8.98	200
Proposed Pruning Learned	-	92.50 ± 0.44		77.28 ± 0.22	100
Proposed Pruning Learned alpha too	-	93.85 ± 0.50		85.53 ± 6.53	100

Table - MCC of a (compressed) simple CNN model on a subset of the MNIST dataset

Soft labelling

Model	Dataset	Soft Labels	Mean MCC	Median MCC
2D CNN	HITS Small	No	86.13 ± 3.80	87.76 ± 1.85
		Yes	87.03 ± 3.55	87.47 ± 1.75
CNN-Transformer		No	85.92 ± 1.79	86.01 ± 0.82
		Yes	86.52 ± 3.73	87.63 ± 0.86
Hybrid		No	92.50 ± 1.36	92.74 ± 0.95
		Yes	93.12 ± 1.00	92.59 ± 0.11
	HITS Large	No	85.49 ± 0.77	85.49 ± 0.77
		Yes	86.77 ± 0.96	86.35 ± 0.49

Datasets MLHC 2022

Datasets MLHC 2022

HITS:

- TCD Data.
- 1545 samples.
- Three classes.
- Sampling frequency: 4385 Hz.

Datasets MLHC 2022

HITS:

- TCD Data.
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Class	Number of samples
Artifact	403
Gaseous Emboli	569
Solid Emboli	569
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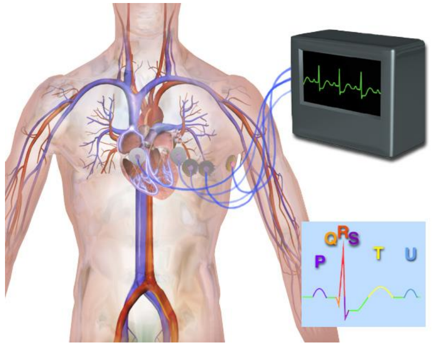

PTB:

- ECG Data.
- 14 552 samples.
- Two classes.
- Sampling frequency: 125 Hz.

Datasets MLHC 2022

HITS:

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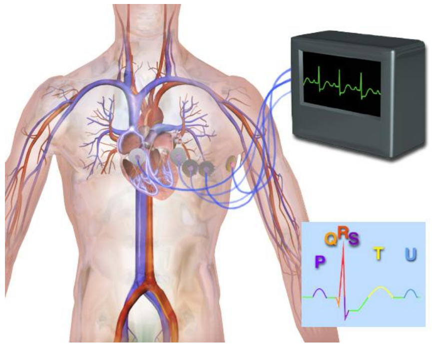
PTB:



- ECG Data.
- 14 552 samples.
- Two classes.
- Sampling frequency: 125 Hz.

Class	Number of samples
Normal	10 506
Abnormal	4 046

Datasets MLHC 2022

HITS:

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- Three classes.
- Sampling frequency: 4385 Hz.

Class	Number of samples
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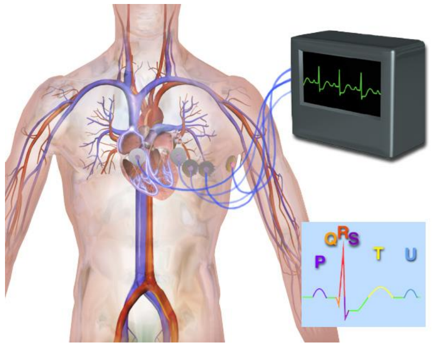

PTB:

- ECG Data.
- 14 552 samples.
- Two classes.
- Sampling frequency: 125 Hz.

Class	Number of samples
Normal	10 506
Abnormal	4 046

MIT-BIH:

- ECG Data.
- 109 436 samples.
- Five classes.
- Sampling frequency: 125 Hz.

Datasets MLHC 2022

HITS:

- TCD Data.
- 1545 samples.
- Three classes.
- Sampling frequency: 4385 Hz.

Class	Number of samples
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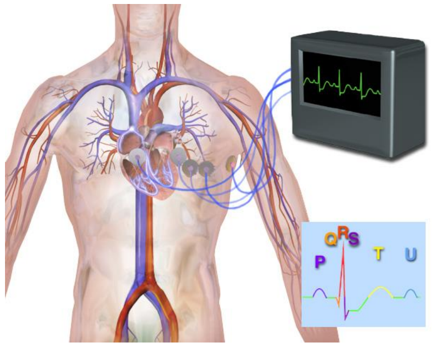

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Class	Number of samples
Normal	10 506
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MIT-BIH:

- ECG Data.
- 109 436 samples.
- Five classes.
- Sampling frequency: 125 Hz.

Class	Number of samples
N	90 589
S	2 779
V	7 226
F	803
Q	8 039

Experiment 1: Advantage of using multiple features
MLHC 2022

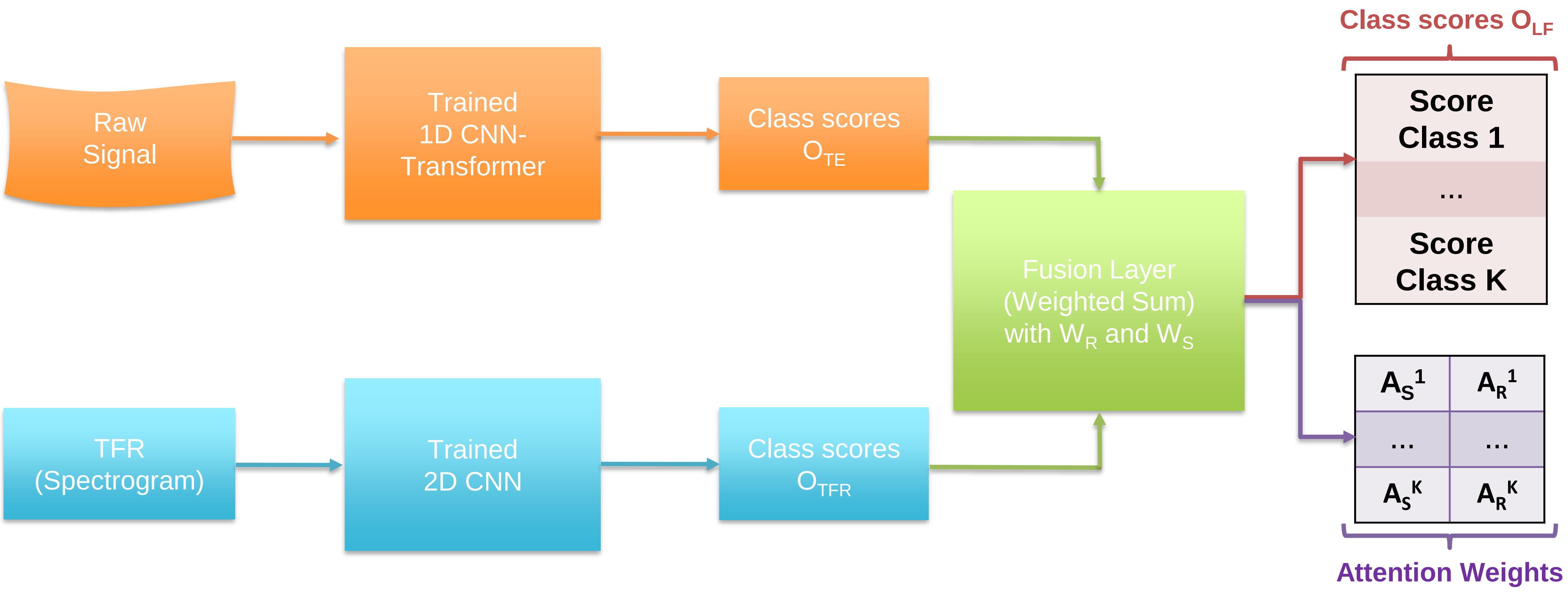

FIGURE - Proposed hybrid CNN Transformer global model

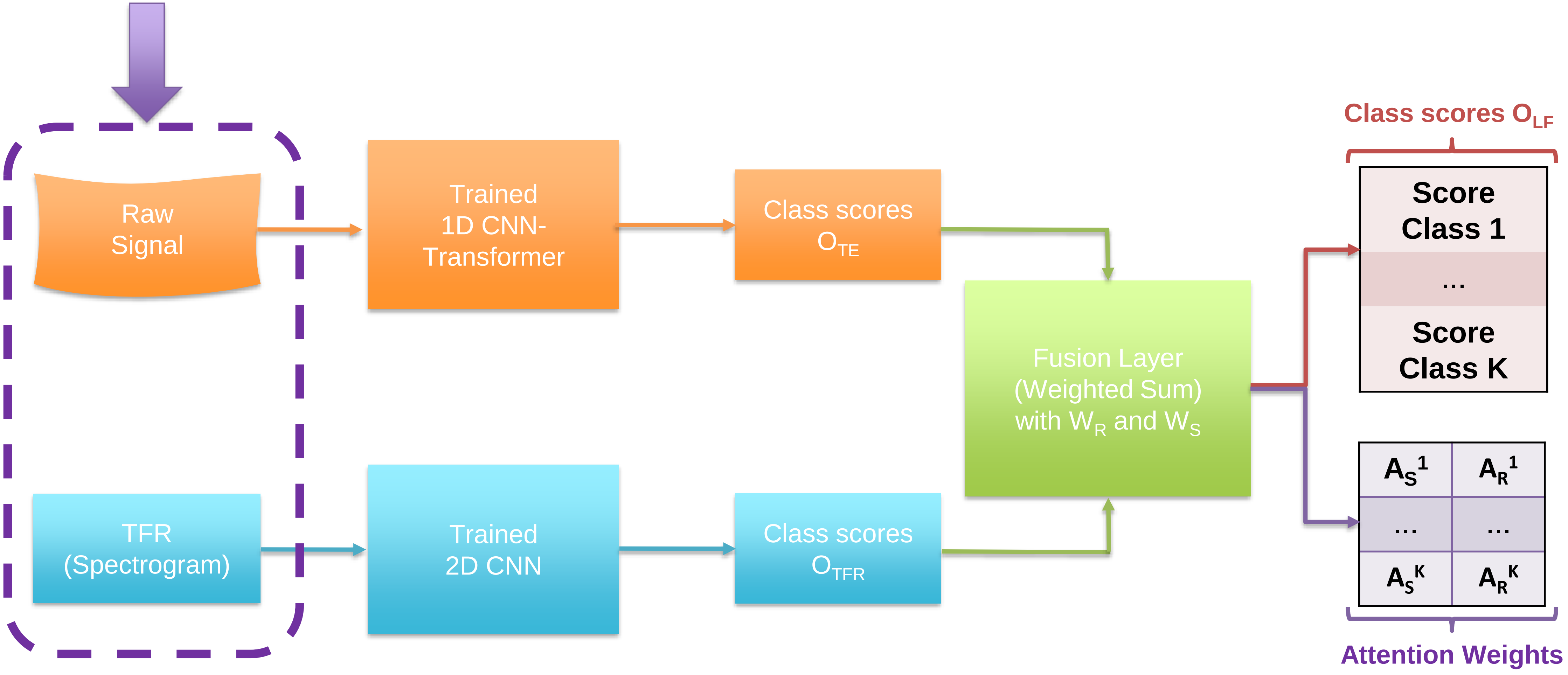

FIGURE - Proposed hybrid CNN Transformer global model

Experimental Setup MLHC 2022

Objective:
- Comparison to **single feature** models.
- Comparison to **SOTA** models.

Models:
- **Single feature models** : 1D CNN-Transformer and 2D CNN.
- **SOTA** : Vindas et al., 2022 (HITS) and Ahmad et al., 2021 (ECG).

Loss function:
- **Cross Entropy** Loss.

Optimizers:
- **ADAM**.
- **NOAM**.

Metrics:
- Matthews Correlation Coefficient (**MCC**).
- **F1-Score**.
- **Accuracy**.

Experimental Setup MLHC 2022

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- Comparison to **SOTA** models.

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Metrics:
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- **F1-Score**.
- **Accuracy**.

For imbalanced datasets

Results MLHC 2022

Dataset	Model	MCC	F1-Score	Accuracy
HITS	2D CNN (previous work)	85.53 ± 2.98	85.68 ± 2.31	89.48 ± 2.06
	1DCNN-Transformer	80.29 ± 1.83	85.36 ± 1.09	87.37 ± 1.23
	2D CNN	85.03 ± 3.06	86.88 ± 2.38	90.55 ± 2.12
	Hybrid	**89.33 ± 2.77**	**91.15 ± 1.97**	**93.39 ± 1.74**
PTB	MIF (Ahmad et al., 2021)	-	-	98.4
	MFF (Ahmad et al., 2021)	-	-	99.2
	1DCNN-Transformer	97.92 ± 0.28	98.96 ± 0.14	99.16 ± 0.11
	2D CNN	93.42 ± 2.27	96.66 ± 1.20	97.32 ± 0.91
	Hybrid	**99.29 ± 0.21**	**99.65 ± 0.10**	**99.71 ± 0.08**
MIT-BIH	MIF (Ahmad et al., 2021)	-	-	98.6
	MFF (Ahmad et al., 2021)	-	-	**99.7**
	1DCNN-Transformer	93.17 ± 0.70	89.44 ± 0.99	97.87 ± 0.24
	2D CNN	91.26 ± 0.76	86.40 ± 1.39	97.34 ± 0.26
	Hybrid	**94.63 ± 0.29**	**91.28 ± 0.54**	98.37 ± 0.09

Results MLHC 2022

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	Hybrid	**89.33 ± 2.77**	**91.15 ± 1.97**	**93.39 ± 1.74**
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Using both representations increase the classification performances of the model in the three datasets

Results MLHC 2022

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	Hybrid	**94.63 ± 0.29**	**91.28 ± 0.54**	98.37 ± 0.09

More stable models (reduced variability), except for the HITS dataset.

Results MLHC 2022

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State-of-the-art results on two datasets.

Experiment 2: Influence of the fusion layer
MLHC 2022

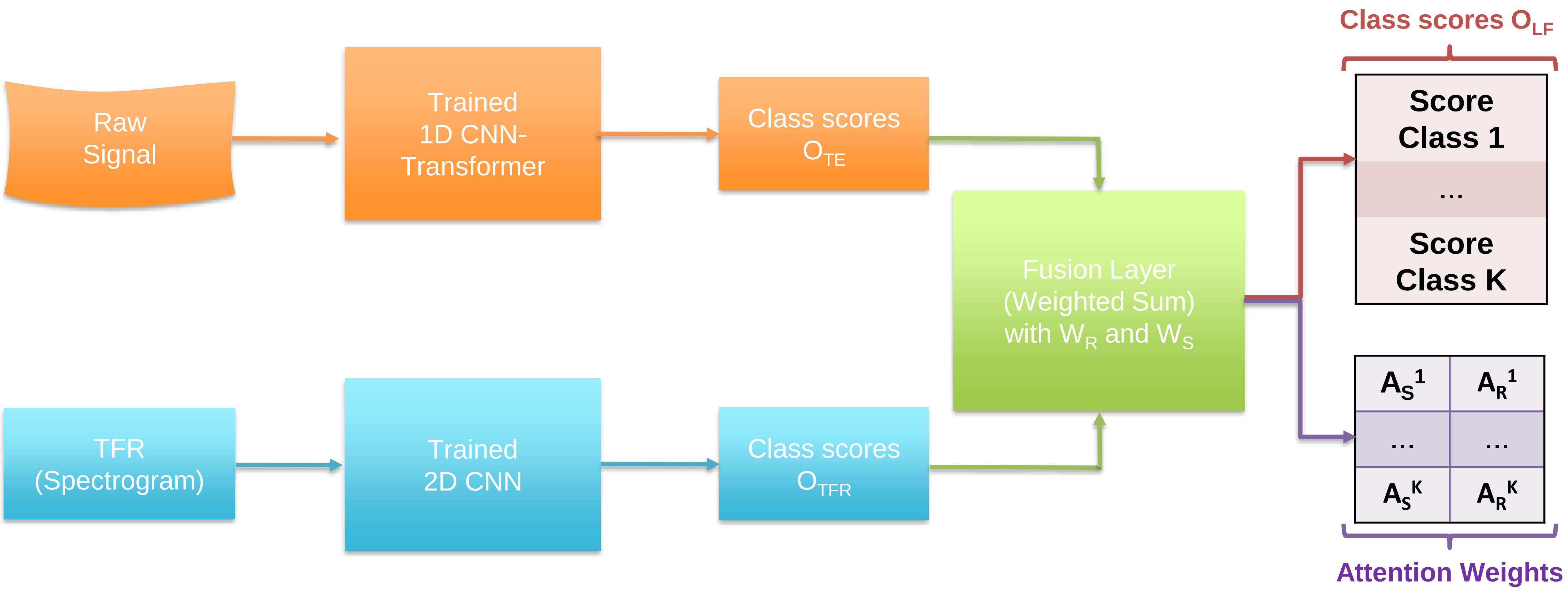

FIGURE - Proposed hybrid CNN Transformer global model

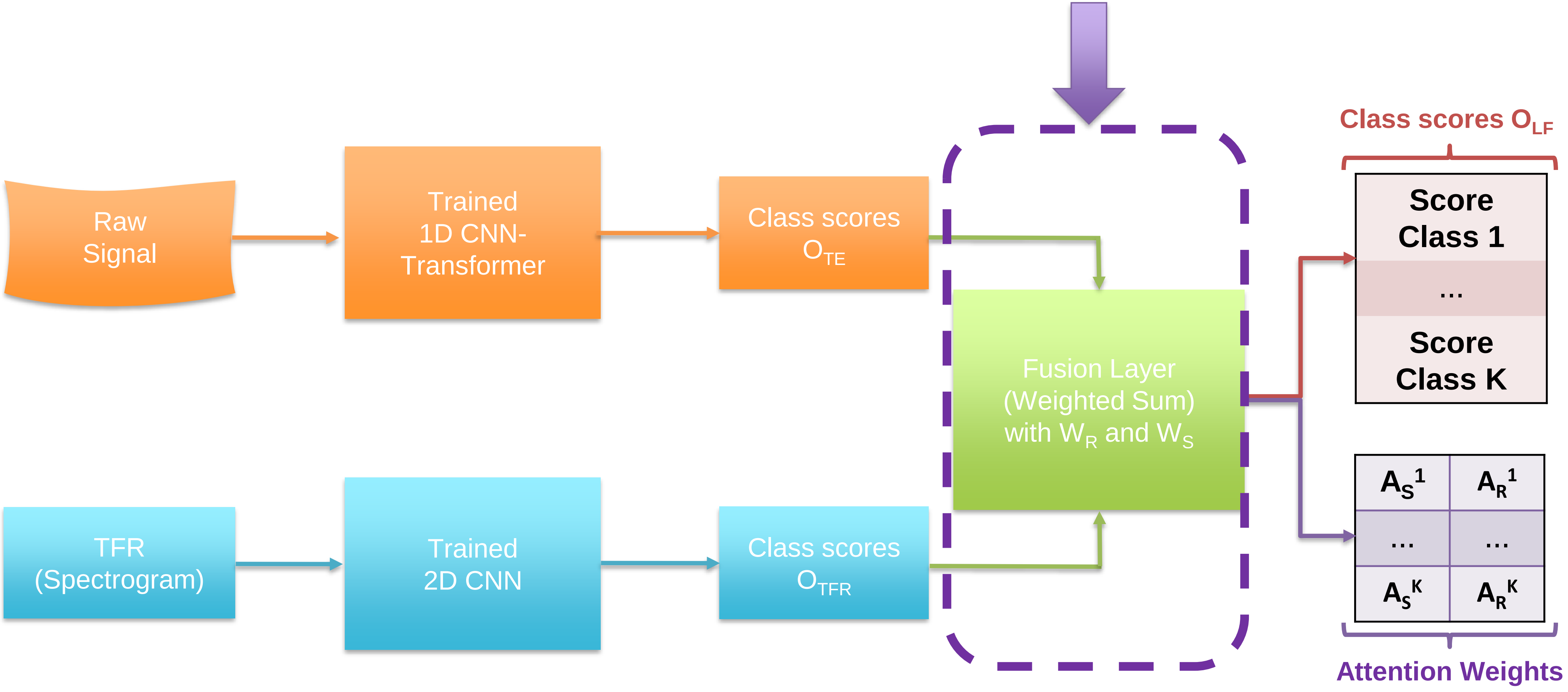

FIGURE - Proposed hybrid CNN Transformer global model

Experimental Setup MLHC 2022

Objective:
- Comparison to **intermediate fusion** models.

Models:
- **Concatenation**.
- **Sum**.
- **Weighted sum**.

Loss function:
- **Cross Entropy** Loss.

Optimizers:
- **NOAM**.

Metrics:
- Matthews Correlation Coefficient (**MCC**).
- **F1-Score**.
- **Accuracy**.

Experimental Setup MLHC 2022

Objective:
- Comparison to **intermediate fusion** models.

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- **Weighted sum**.

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Optimizers:
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Metrics:
- Matthews Correlation Coefficient (**MCC**).
- **F1-Score**.
- **Accuracy**.

For imbalanced datasets

Results MLHC 2022

Dataset	Fusion Type	MCC	F1-Score	Accuracy
HITS	Concatenation	84.96 ± 2.54	86.37 ± 2.11	90.62 ± 1.65
	Sum	89.04 ± 1.98	90.23 ± 1.71	93.16 ± 1.29
	Weighted Sum	86.31 ± 2.80	87.73 ± 2.32	91.31 ± 1.92
	Hybrid	**89.33 ± 2.77**	**91.15 ± 1.97**	**93.39 ± 1.74**
PTB	Concatenation	92.91 ± 2.61	96.42 ± 1.33	97.11 ± 1.05
	Sum	92.12 ± 2.33	96.02 ± 1.19	96.78 ± 0.99
	Weighted Sum	92.74 ± 2.01	96.35 ± 1.00	97.06 ± 0.81
	Hybrid	**99.29 ± 0.21**	**99.65 ± 0.10**	**99.71 ± 0.08**
MIT-BIH	Concatenation	91.51 ± 0.79	86.93 ± 1.10	97.42 ± 0.27
	Sum	91.89 ± 0.47	87.50 ± 0.87	97.55 ± 0.15
	Weighted Sum	91.56 ± 0.72	86.70 ± 1.13	97.44 ± 0.24
	Hybrid	**94.63 ± 0.29**	**91.28 ± 0.54**	98.37 ± 0.09

Results MLHC 2022

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	Hybrid	**94.63 ± 0.29**	**91.28 ± 0.54**	98.37 ± 0.09

The best fusion method is the late proposed method for the three datasets.

Results MLHC 2022

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	Hybrid	**94.63 ± 0.29**	**91.28 ± 0.54**	98.37 ± 0.09

For the HITS dataset: the intermediate sum fusion method achieve similar performances as the late hybrid fusion method

Results MLHC 2022

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	Sum	92.12 ± 2.33	96.02 ± 1.19	96.78 ± 0.99
	Weighted Sum	92.74 ± 2.01	96.35 ± 1.00	97.06 ± 0.81
	Hybrid	**99.29 ± 0.21**	**99.65 ± 0.10**	**99.71 ± 0.08**
MIT-BIH	Concatenation	91.51 ± 0.79	86.93 ± 1.10	97.42 ± 0.27
	Sum	91.89 ± 0.47	87.50 ± 0.87	97.55 ± 0.15
	Weighted Sum	91.56 ± 0.72	86.70 ± 1.13	97.44 ± 0.24
	Hybrid	**94.63 ± 0.29**	**91.28 ± 0.54**	98.37 ± 0.09

- The other fusion methods have similar performances for the three datasets.
- Worst performances than the best single feature model of experiment 1.

Results MLHC 2022

Results MLHC 2022

Attention weights for the HITS dataset

Results MLHC 2022

Class	Spectrogram	Raw Signal
Artifacts	0.46 ± 0.29	0.54 ± 0.29
Gaseous Emboli	0.65 ± 0.17	0.35 ± 0.17
Solid Emboli	0.71 ± 0.15	0.29 ± 0.15

Attention weights for the HITS dataset

Results MLHC 2022

Class	Spectrogram	Raw Signal
Artifacts	0.46 ± 0.29	0.54 ± 0.29
Gaseous Emboli	0.65 ± 0.17	0.35 ± 0.17
Solid Emboli	0.71 ± 0.15	0.29 ± 0.15

Attention weights for the HITS dataset

Attention weights for the PTB dataset

Results MLHC 2022

Class	Spectrogram	Raw Signal
Artifacts	0.46 ± 0.29	0.54 ± 0.29
Gaseous Emboli	0.65 ± 0.17	0.35 ± 0.17
Solid Emboli	0.71 ± 0.15	0.29 ± 0.15

Attention weights for the HITS dataset

Class	Spectrogram	Raw Signal
Normal	0.49 ± 0.12	0.51 ± 0.12
Abnormal	0.18 ± 0.10	0.82 ± 0.10

Attention weights for the PTB dataset

Results MLHC 2022

Class	Spectrogram	Raw Signal
Artifacts	0.46 ± 0.29	0.54 ± 0.29
Gaseous Emboli	0.65 ± 0.17	0.35 ± 0.17
Solid Emboli	0.71 ± 0.15	0.29 ± 0.15

Attention weights for the HITS dataset

Class	Spectrogram	Raw Signal
Normal	0.49 ± 0.12	0.51 ± 0.12
Abnormal	0.18 ± 0.10	0.82 ± 0.10

Attention weights for the PTB dataset

Attention weights for the MIT-BIH dataset

Results MLHC 2022

Class	Spectrogram	Raw Signal
Artifacts	0.46 ± 0.29	0.54 ± 0.29
Gaseous Emboli	0.65 ± 0.17	0.35 ± 0.17
Solid Emboli	0.71 ± 0.15	0.29 ± 0.15

Attention weights for the HITS dataset

Class	Spectrogram	Raw Signal
Normal	0.49 ± 0.12	0.51 ± 0.12
Abnormal	0.18 ± 0.10	0.82 ± 0.10

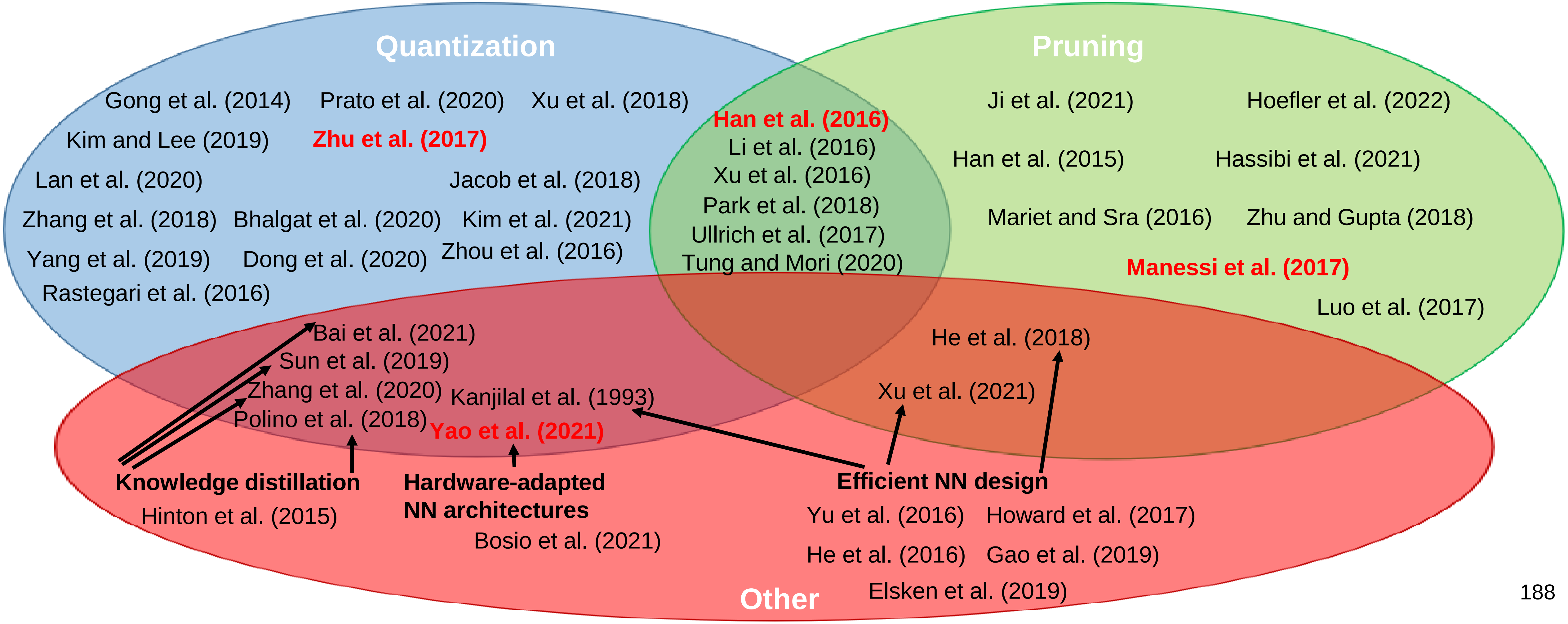
Attention weights for the PTB dataset

Class	Spectrogram	Raw Signal
N	0.48 ± 0.01	0.52 ± 0.01
S	0.50 ± 0.01	0.50 ± 0.01
V	0.50 ± 0.01	0.50 ± 0.01
F	0.49 ± 0.02	0.51 ± 0.02
Q	0.50 ± 0.003	0.50 ± 0.003

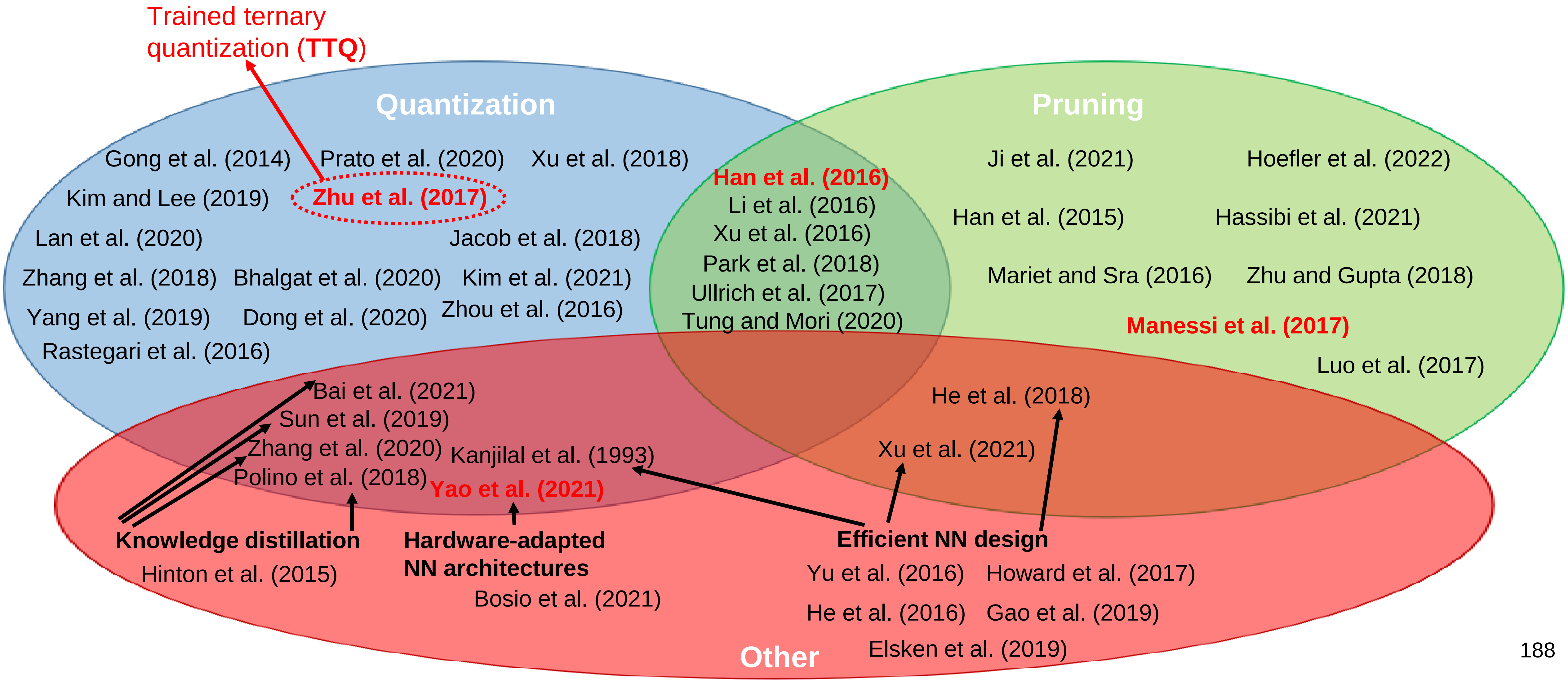
Attention weights for the MIT-BIH dataset

Contribution 3 : Model compression based on extreme quantization

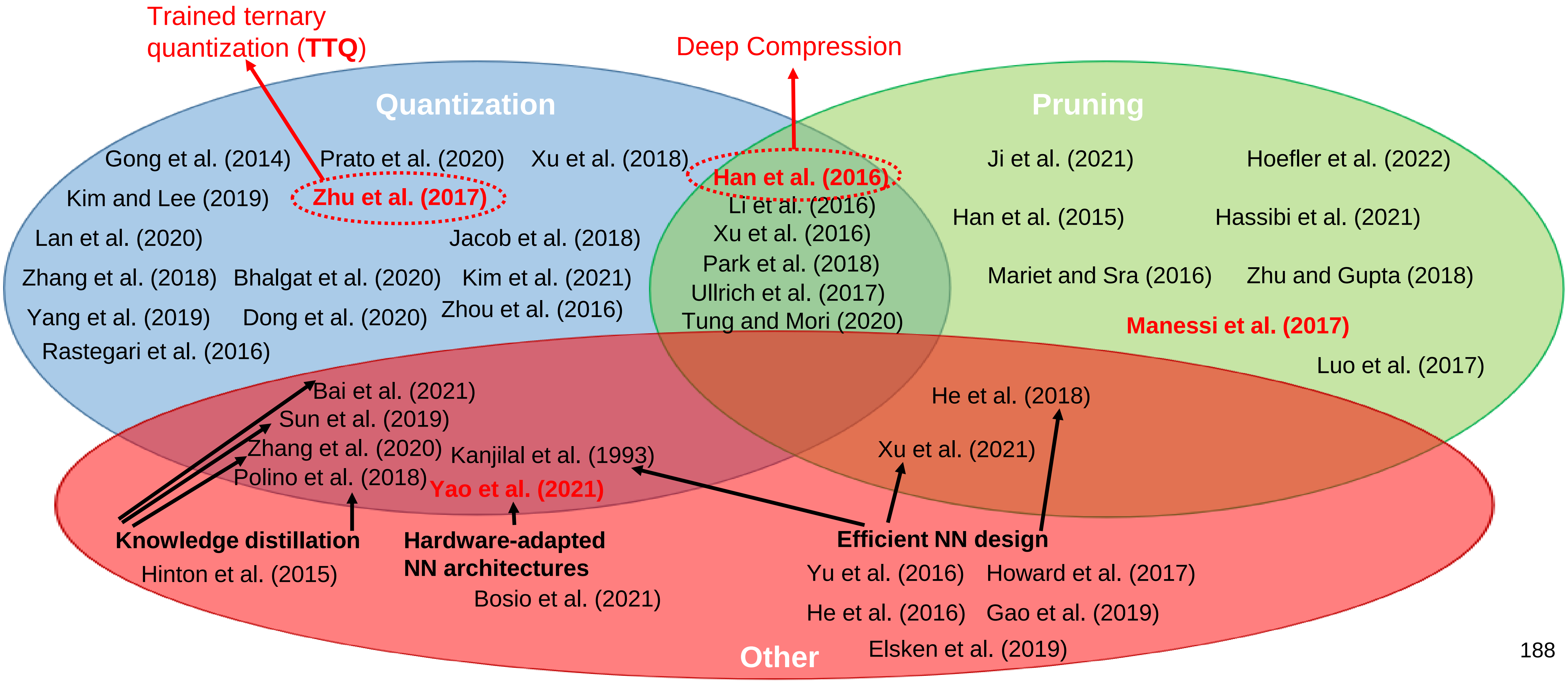
General Overview



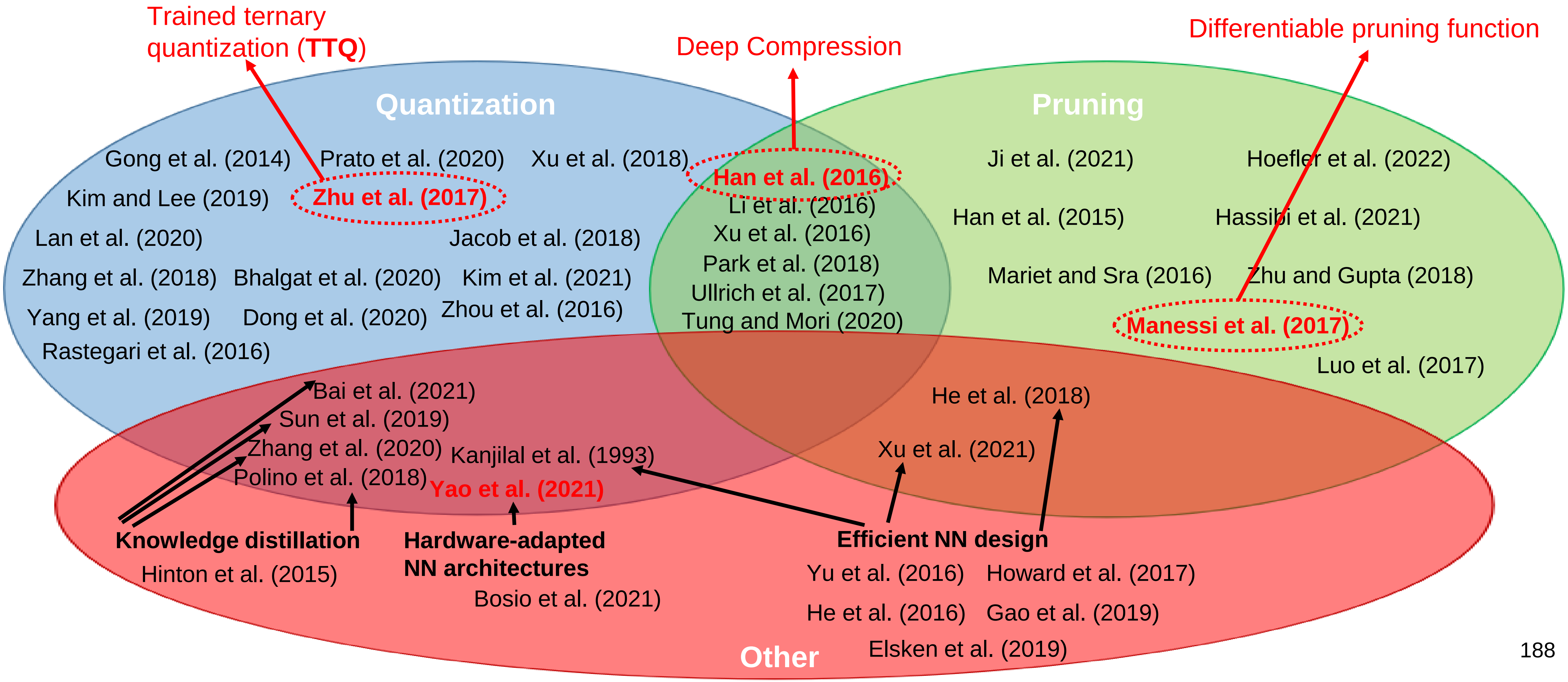
General Overview



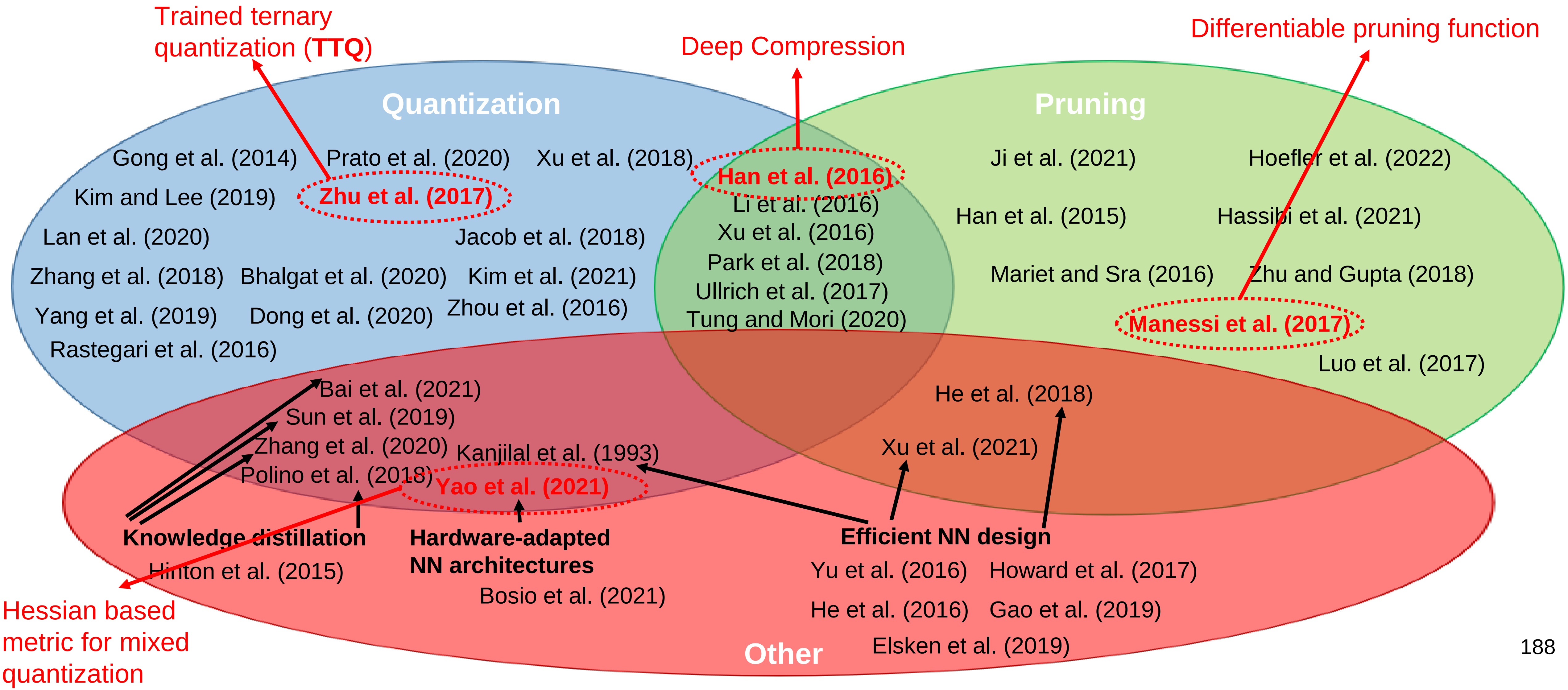
General Overview



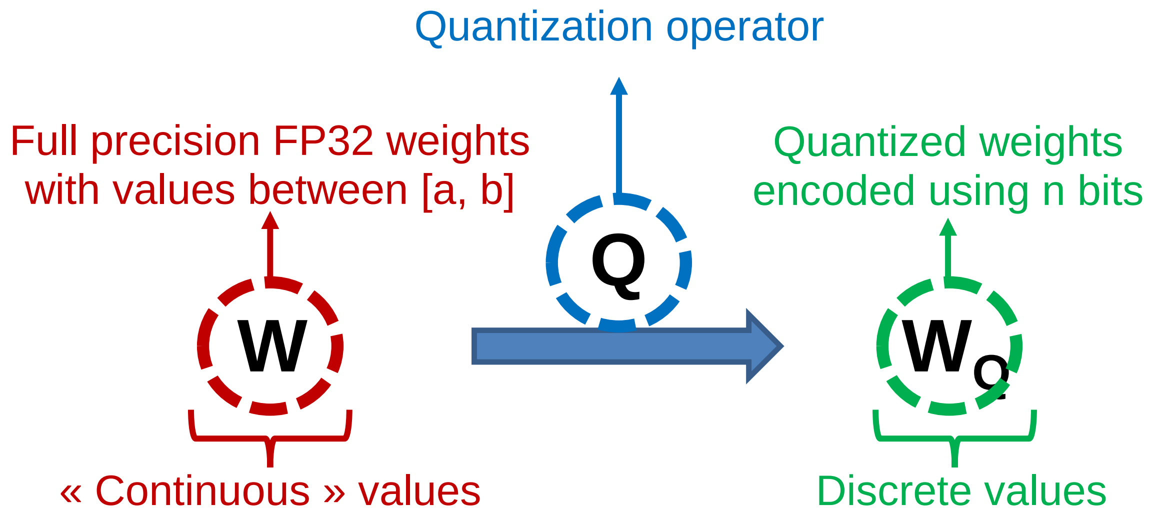
General Overview



General Overview

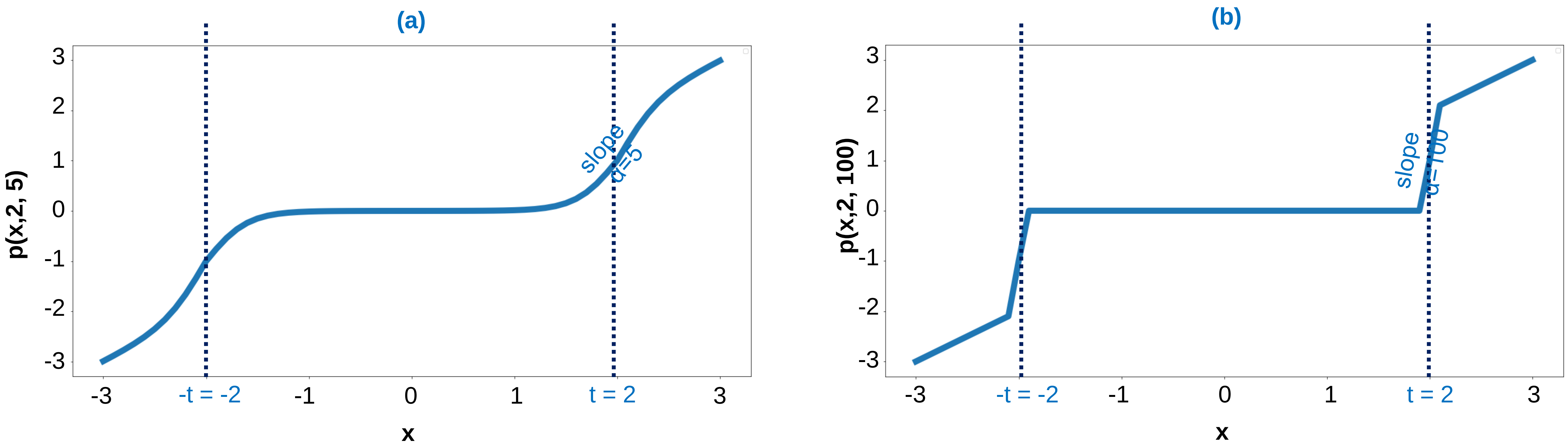


Quantization principle



- **Clipping range** : interval [a, b] where the values of **W** live.
- **Calibration** : step of clipping range search.
- **Scaling factor S** : Number of partitions of the clipping range to use.

Differentiable pruning function



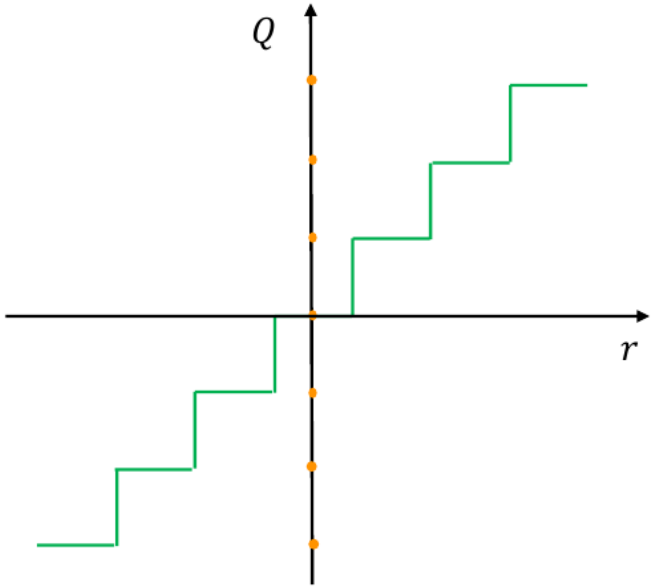
$$\forall x, t, \alpha \in \mathbb{R}, p(x; t, \alpha) = [ReLU(x - t) + t \times \sigma(\alpha \times (x - t)] + [-ReLU(-x - t) - t \times \sigma(\alpha \times (-x - t))]$$

Figure – Differentiable pruning function (**Manessi et al. 2017**)

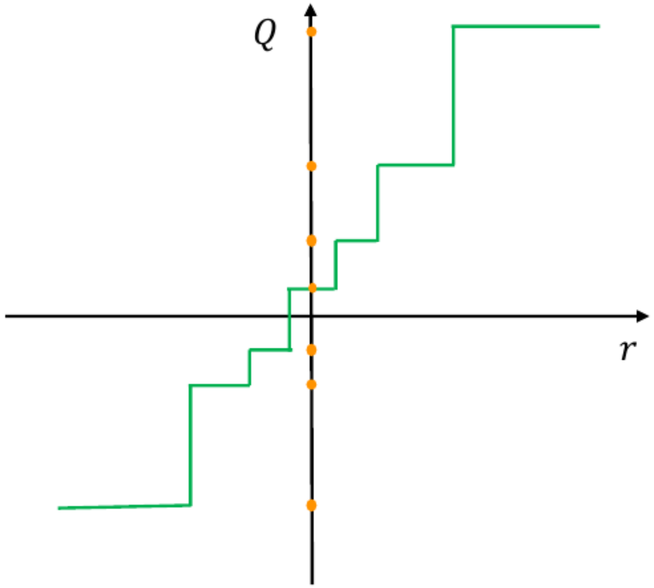
Quantization

Uniform vs non-uniform :

+ Easier to deploy
- Worst classification performances



Uniform



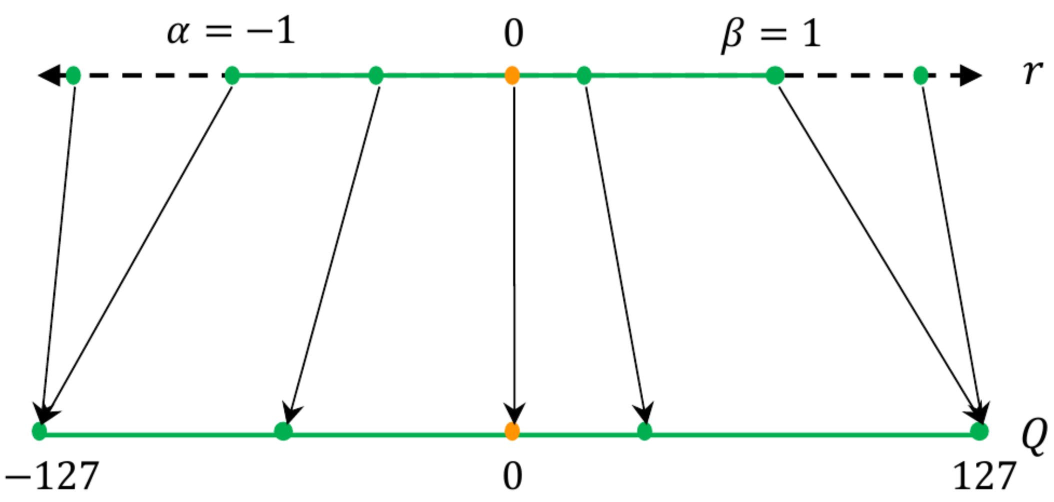
Non-uniform

+ Higher classification performances
- More difficult to deploy

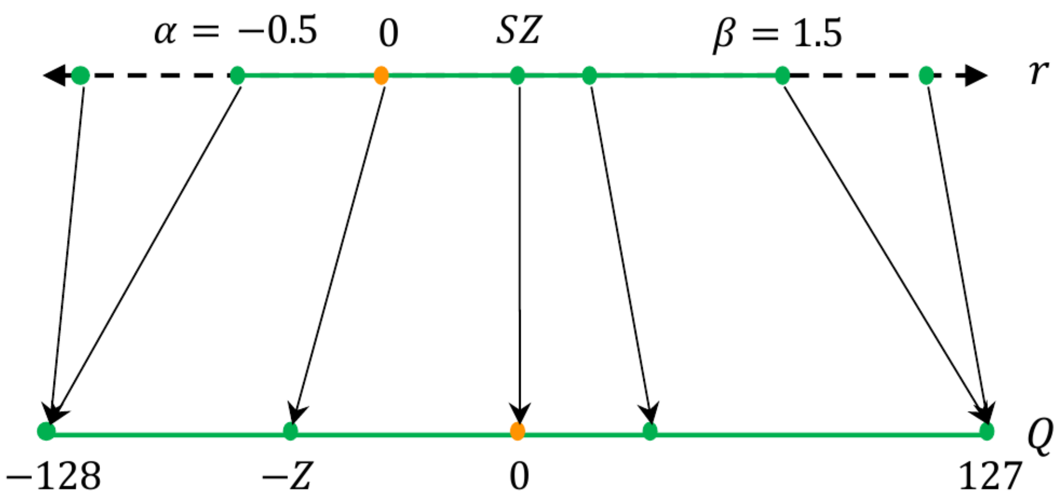
Quantization

Symmetric vs asymmetric :

Symmetric



Asymmetric



+ Easier to implement
+ Reduce computational cost
- Not adapted to imbalanced weights/activations
- Worst classification performances

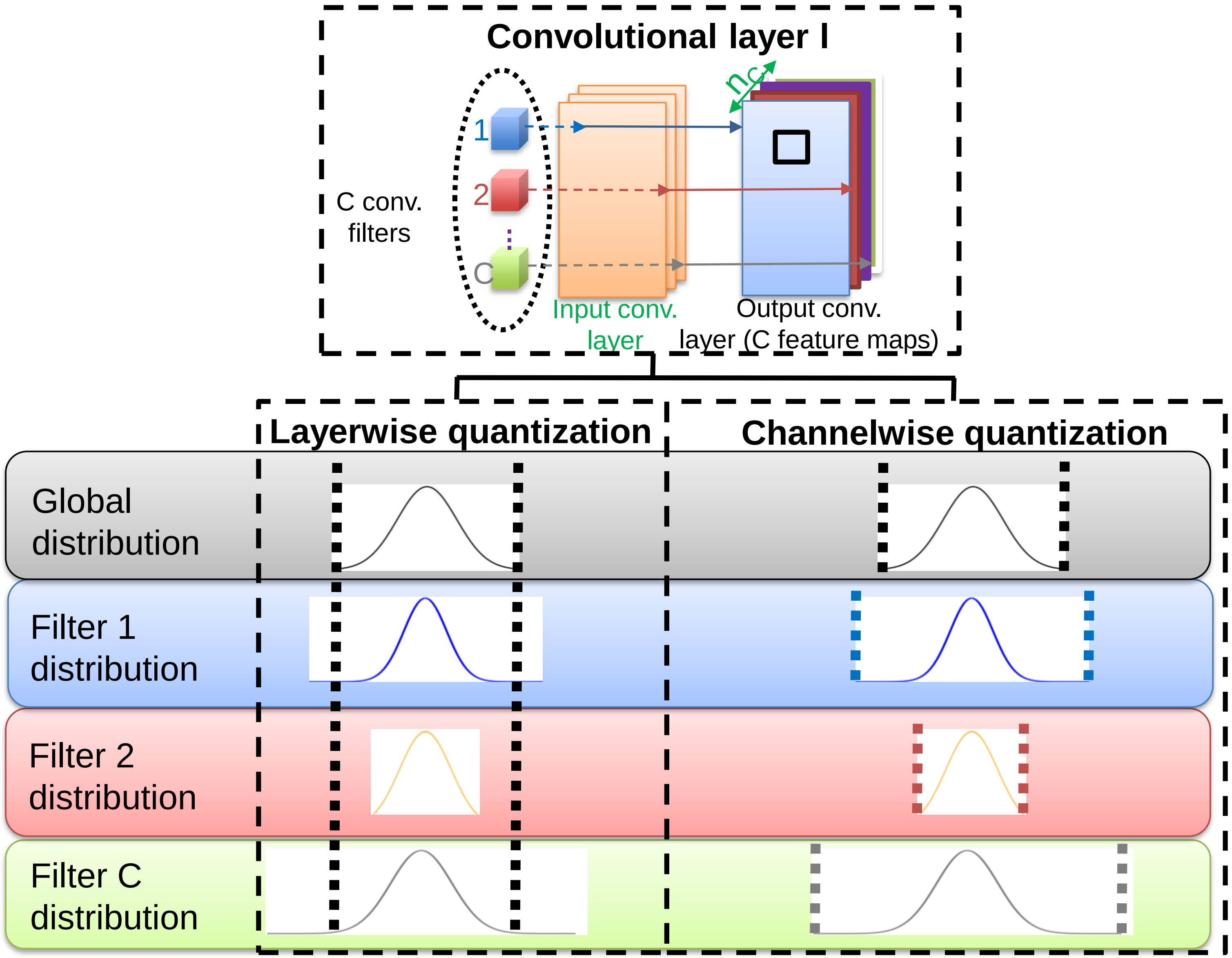
+ Better classification performances
+ Adapted for imbalanced weights/activations
- More difficult to implement
- More computationally expensive

Quantization

Static vs dynamic (w.r.t. clipping range) :

Static	Dynamic
Clipping range pre-computed before inference	Clipping range computed dynamically during inference
+ Less computation resources	+ Higher performances
- Lower performances	- Computationally expensive
==> Most commonly used	

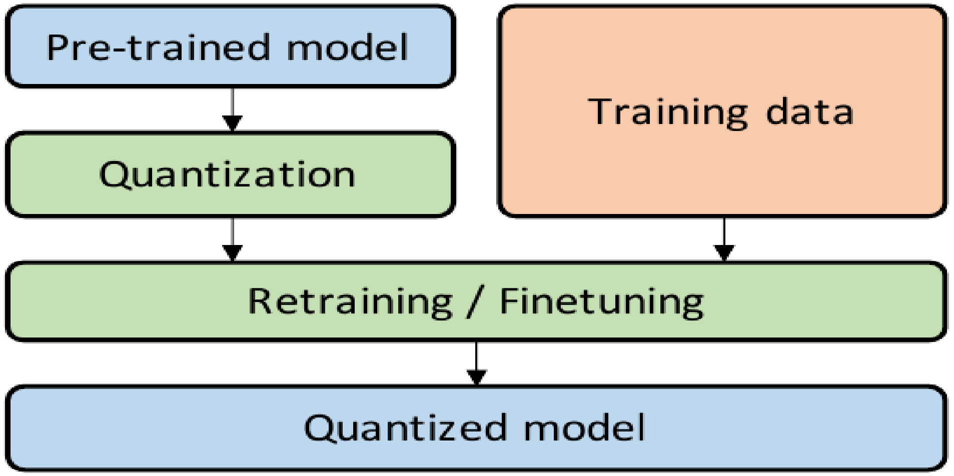
Quantization granularities



Quantization

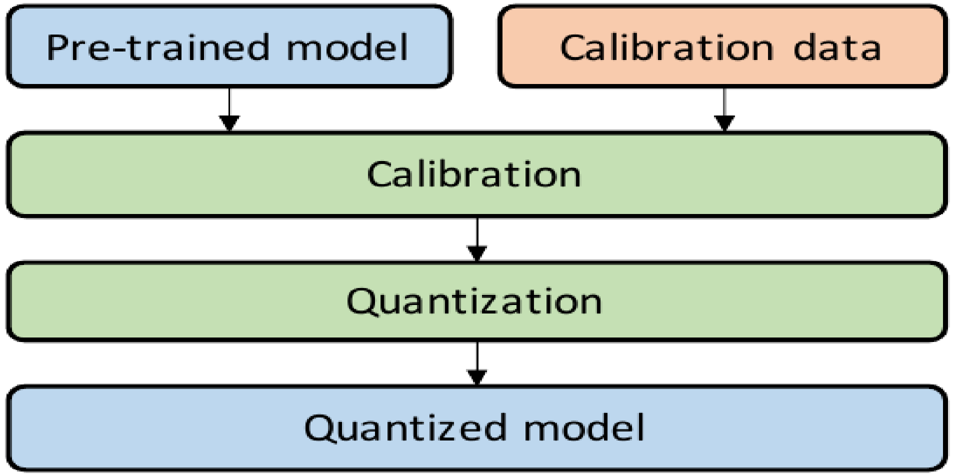
QAT vs PTQ vs ZSQ :

Quantized Aware Training (QAT)



+ Higher classification performances
~ Be careful with gradient computation
- Expensive during training

Post-Training Quantization



+ Does not modify the training procedure
- Lower classification performances

Types of quantization approaches (Gholami et al. 2021)

- QAT vs PTQ vs ZSQ :
  - Zero-Shot Quantization:
    - No need of training, validation or testing data.
    - Good when we do not have access to the original training data.
  - Can be mixed with QAT and PTQ:
    - No data + fine-tuning ==> ZSQ + PTQ.
      - Correcting biases introduced in the quantized weights.
    - No data + fine-tuning ==> ZSQ + QAT
      - Ex.: use of synthetic data.

Quantization

Stochastic vs deterministic :

Stochastic

$$Q(W) = \begin{cases} W_Q \text{ with probability } p \\ W_{Q'} \text{ with probability } 1-p \end{cases}$$

+ Higher classification performances
~ Choice of the stochastic strategy
- Overhead due to the generation of random numbers

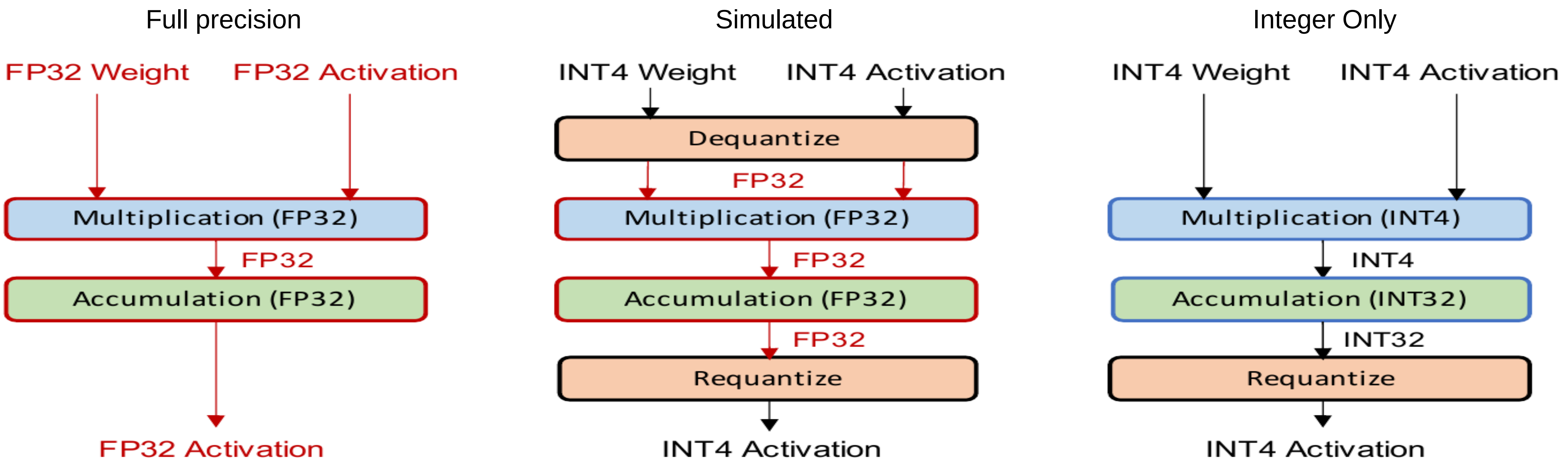
Deterministic

$$Q(W) = w_Q$$

+ Less computationally expensive
+ “Easier” to optmize
- Lower classification performances

Quantization

Simulated vs Integer-only :



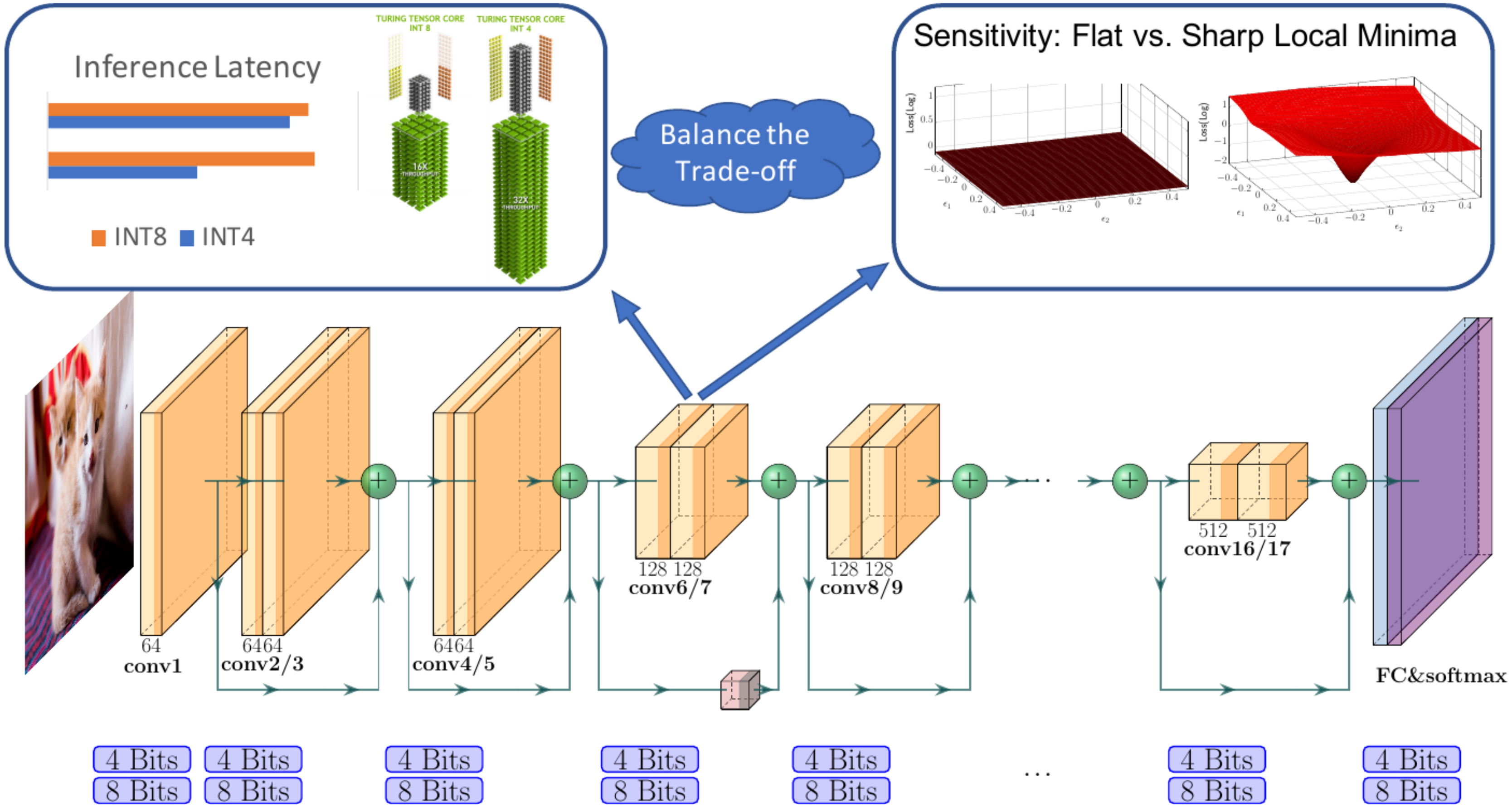
Simulated :
+ Better classification performances
- Does not benefit from low-precision logic

Integer-only :
+ Benefits from low-precision logic
- Lower classification performances
- Most works are limited to ReLU activations

Quantization

Mixed precision :

- Reinforcement learning approaches.
- NAS approaches.
- Regularization approaches.
- Hessian approaches.



HAWQ

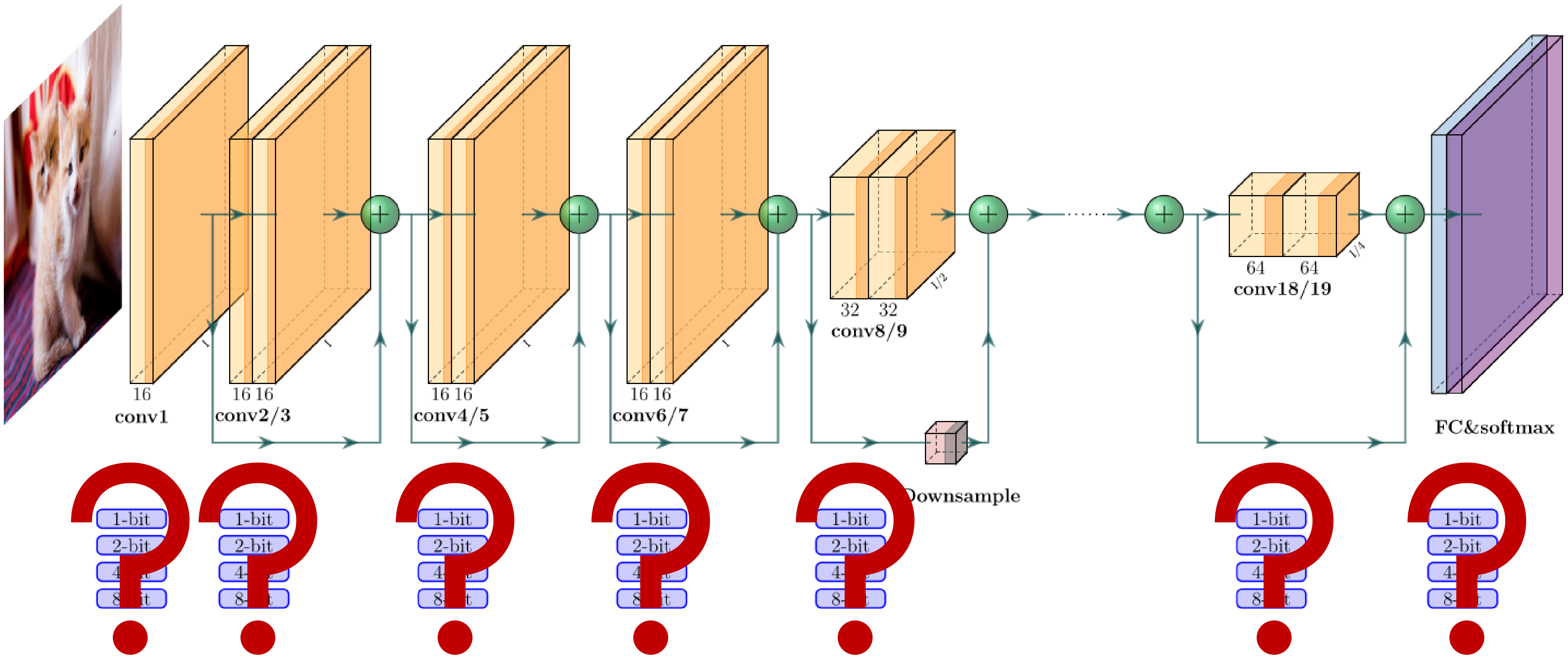


Figure – Hessian aware trace weighted quantization (HAWQ) for mixed quantization (**Dong et al. 2020**)

HAWQ

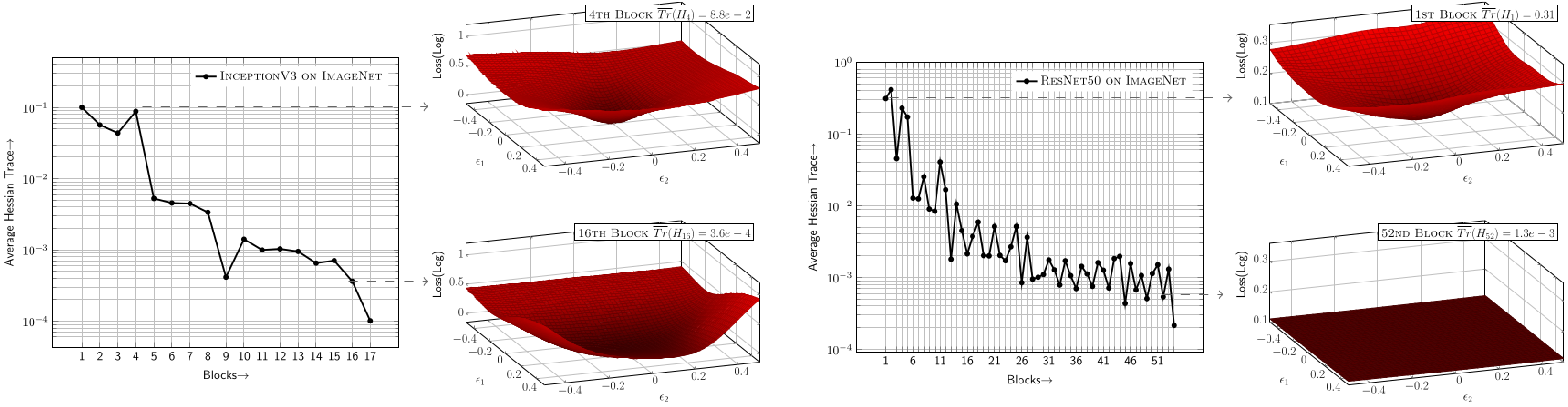


Figure – Hessian aware trace weighted quantization (HAWQ) for mixed quantization (**Dong et al. 2020**)

Ternary Weight Networks and DoReFa-Net

w → Full precision weight tensor

Ternary Weights Network

Binary Weights DoReFa-Net

$$w_l^t = \begin{cases} W_l : \tilde{w}_l > \Delta_l \\ 0 : |\tilde{w}_l| \leq \Delta_l \\ -W_l : \tilde{w}_l < -\Delta_l \end{cases}$$

$$w^b = \boldsymbol{E}(|\tilde{w}|) \times \mathrm{sign}(\tilde{w})$$

$$\Delta_l = 0.7 \times \boldsymbol{E}(|\tilde{w}_l|)$$

$$W_l = \underset{i \in \{i | \tilde{w}_l(i)| > \Delta\}}{\boldsymbol{E}} (|\tilde{w}_l(i)|)$$

Compression evaluation metrics

Sparsity-based metric

Full precision model

Quantized model

Function counting the number of quantized weights having a value of 0

$$SRQW(\mathcal{M}_{FP}, \mathcal{M}_C) = \frac{nzqw(\mathcal{M}_C)}{nqw(\mathcal{M}_{FP})}$$

Function counting the number of weights that can be quantized

Compression-based metrics

Function counting the number of bits necessary to store the weights (using COO sparse storage format)

$$CR(\mathcal{M}_{FP}, \mathcal{M}_Q) = \frac{nbits(\mathcal{M}_Q)}{nbits(\mathcal{M}_{FP})} \; ; \; CR_G(\mathcal{M}_{FP}, \mathcal{M}_Q) = 1 - CR(\mathcal{M}_{FP}, \mathcal{M}_Q)$$

Energy consumption evaluation metrics

Energy of mult-adds

Number of nonzero mult-adds

$$EC_{MA}(\mathcal{M}) = N_{MA} \times 3.7 \times 10^{-12}$$

Order of magnitude of the energy cost of a 32-bit multiplication (Horowitz et al. 2014)

Energy consumption evaluation metrics

Energy of data transfers

Number of layers in the model

Current layer

Number of bits necessary to encode the weights of the layer

$$EC_{DT}(\mathcal{M}) = 10^{-9} \times \sum_{i=1}^{p} \left(\left\lceil \frac{nnzw(L_i) \times B_i}{32} \right\rceil + N_{SF}^{i} \right)$$

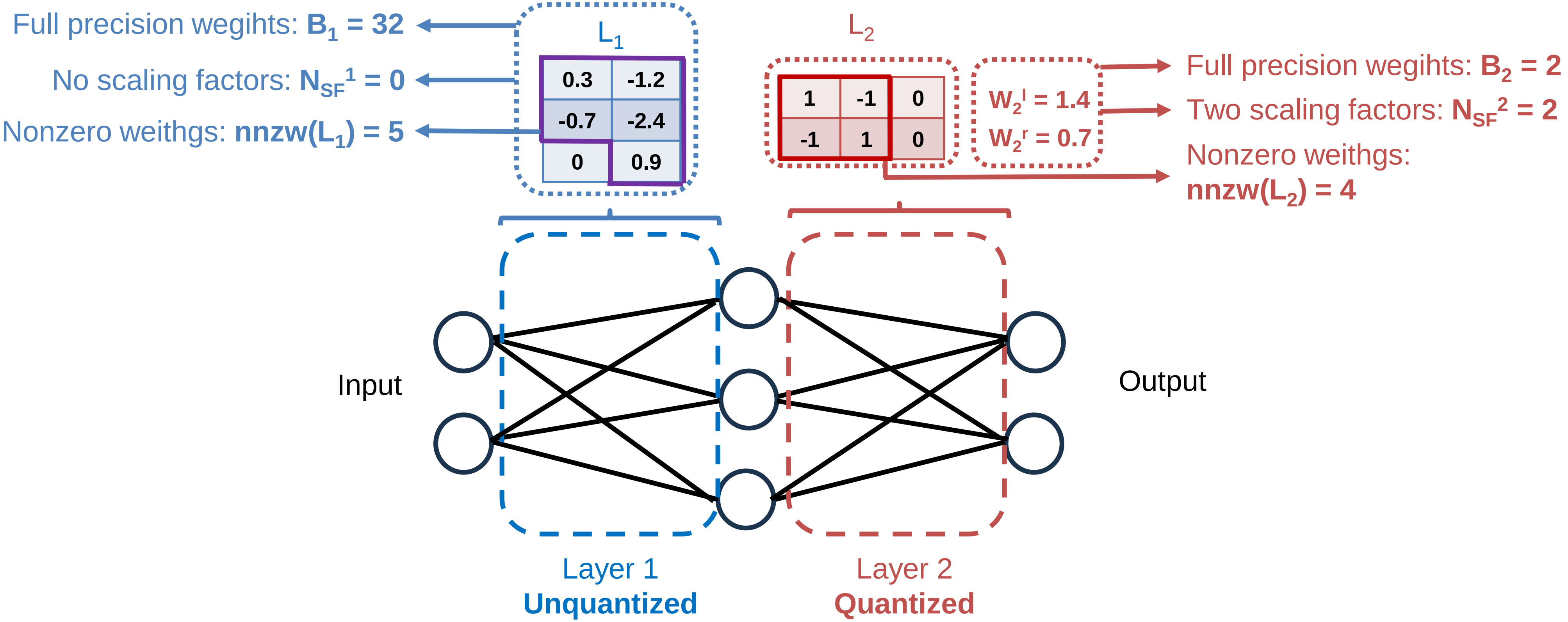
Order of magnitude of data transfers to memory from Molka et al. (2010)

Number of scaling factors

Function counting the number of nonzero weights

Energy consumption evaluation metrics

Energy of data transfers



$$EC_{DT}(\mathcal{M}) = 10^{-9} \times [(\lceil \frac{nnzw(L_1) \times B_1}{32} \rceil + N_{SF}^1) + (\lceil \frac{nnzw(L_2) \times B_2}{32} \rceil + N_{SF}^2)] = 10^{-9} \times [(\lceil \frac{5 \times 32}{32} \rceil + 0) + (\lceil \frac{4 \times 2}{32} \rceil + 2)]$$

$$= 10^{-9} \times [(5+0) + (1+2)] = 8 \times 10^{-9} \quad J$$

Energy consumption evaluation metrics

Total energy

Takes into account sparsity

$$EC_T(\mathcal{M}) = EC_{MA}(\mathcal{M}) + EC_{DT}(\mathcal{M})$$

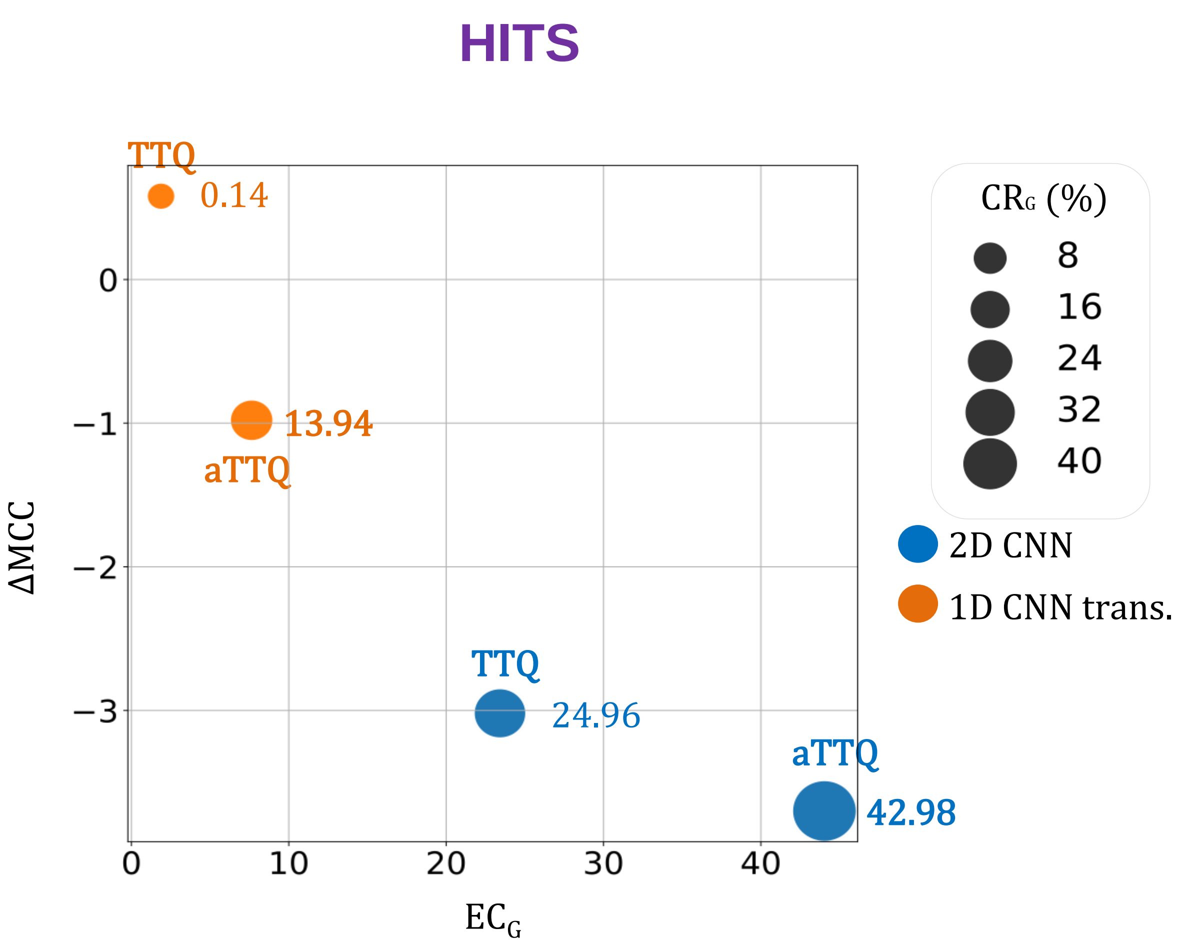
Takes into account sparsity AND reduced precision

$$EC^T_G(\mathcal{M}_{FP}, \mathcal{M}_C) = \frac{|EC_T(\mathcal{M}_{FP}) - EC_T(\mathcal{M}_C)|}{EC_T(\mathcal{M}_{FP})}$$

Takes into account sparsity

The higher the better

Experiment: SOTA comparison



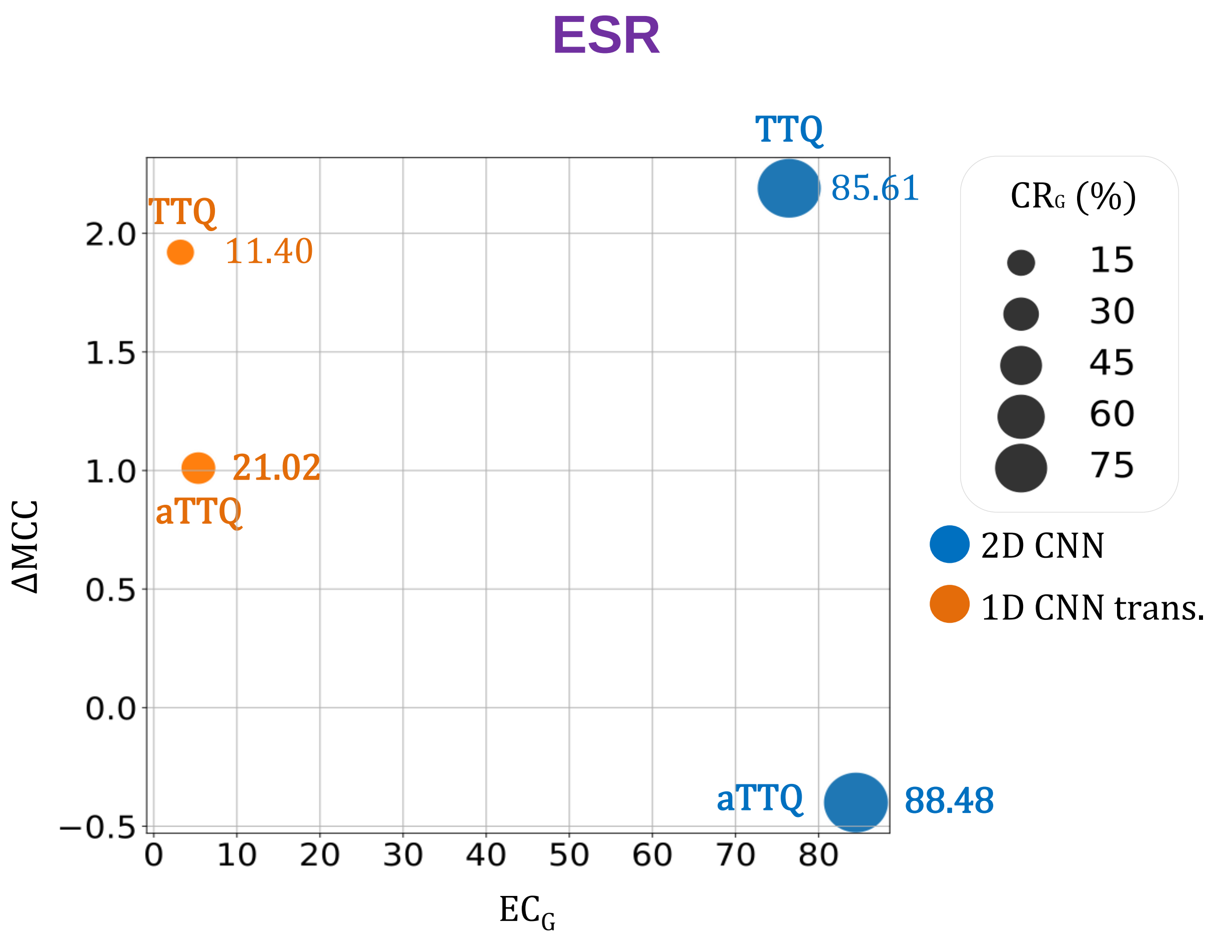
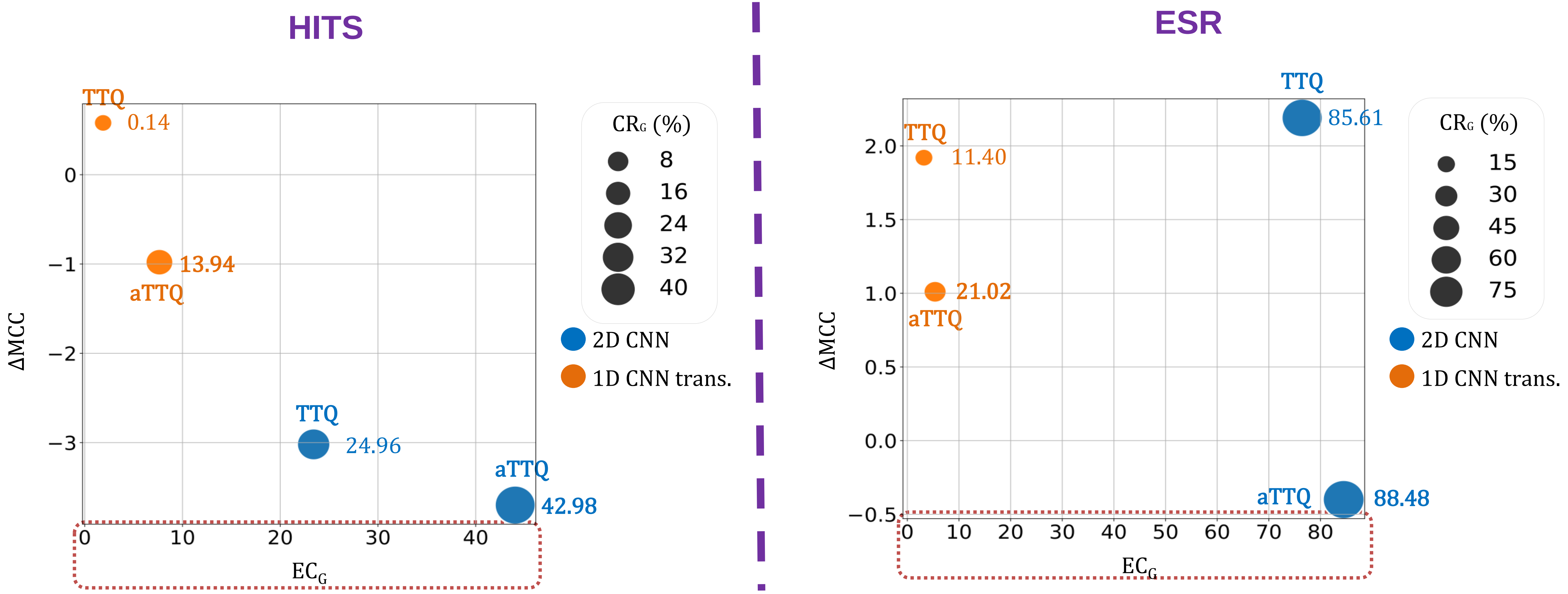


Figure – Comparison of aTTQ with FP and TTQ

Experiment: SOTA comparison

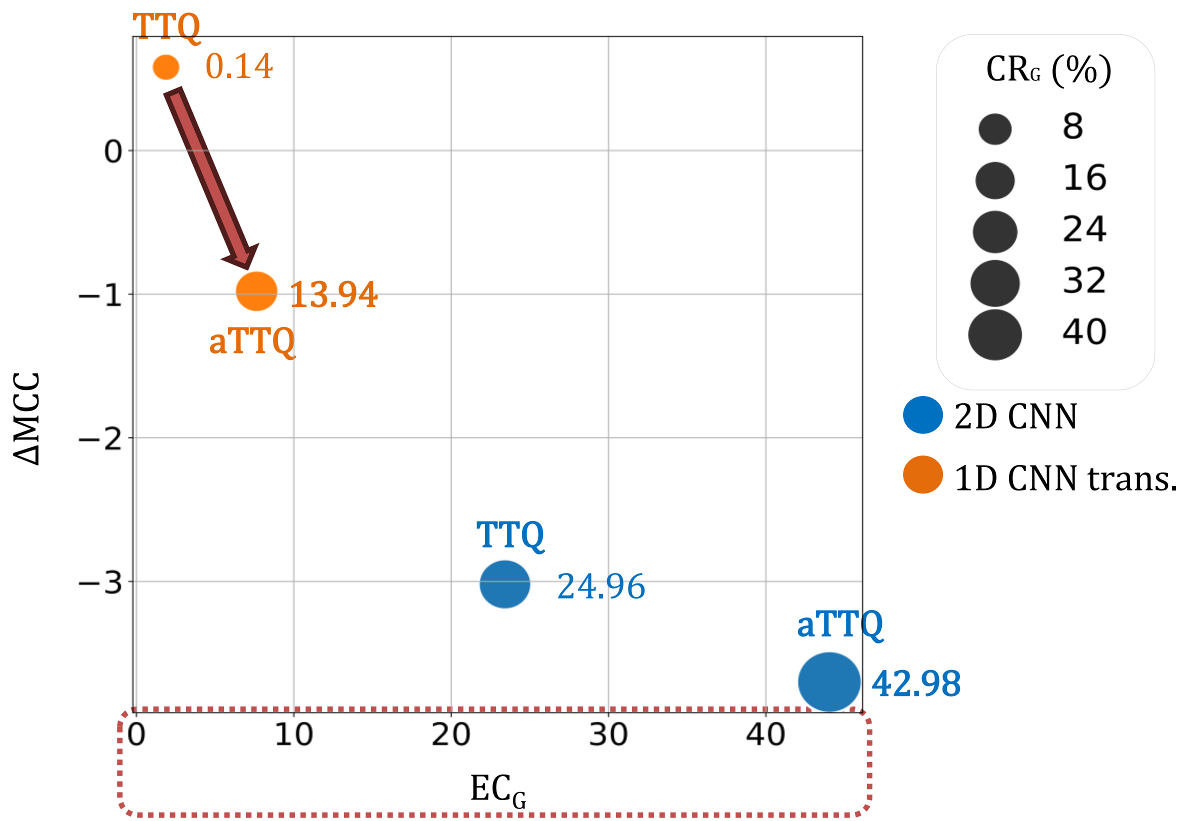


aTTQ always have higher energy consumption gains compared to TTQ.

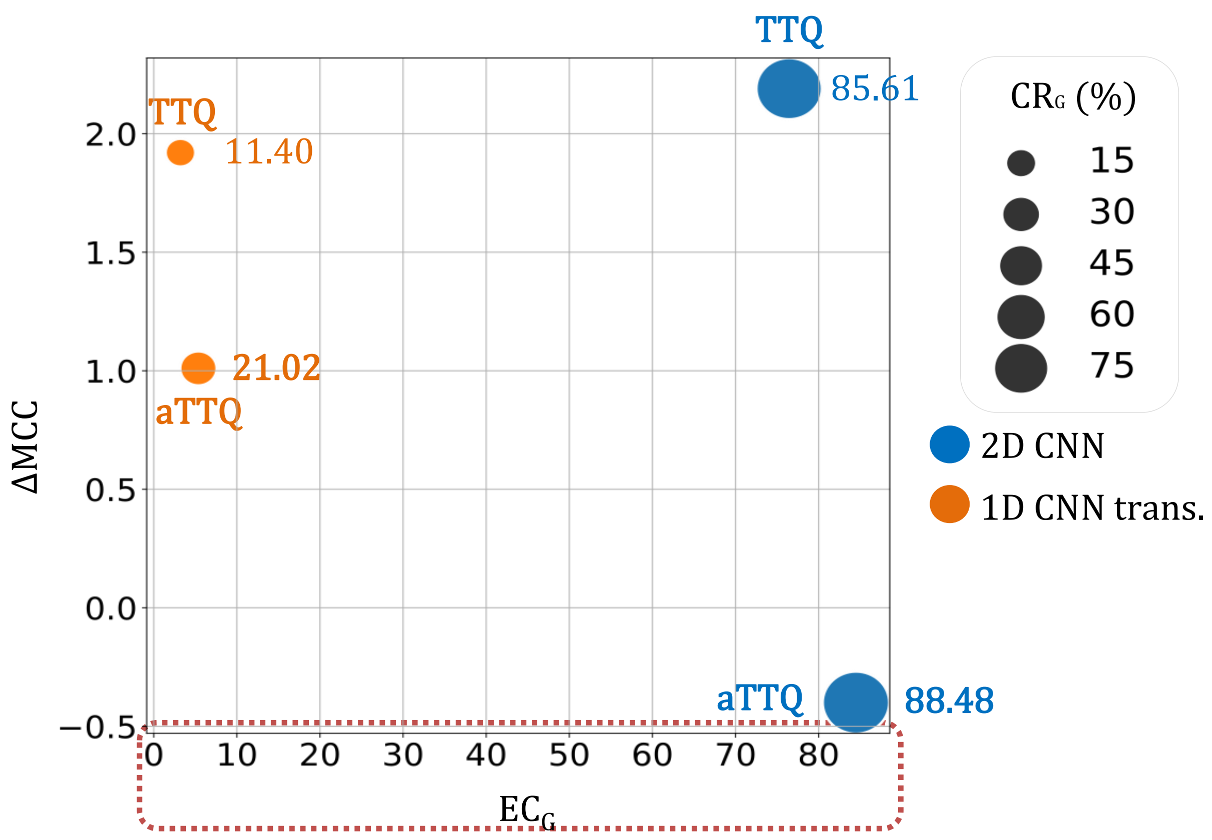
Figure – Comparison of aTTQ with FP and TTQ

Experiment: SOTA comparison

HITS



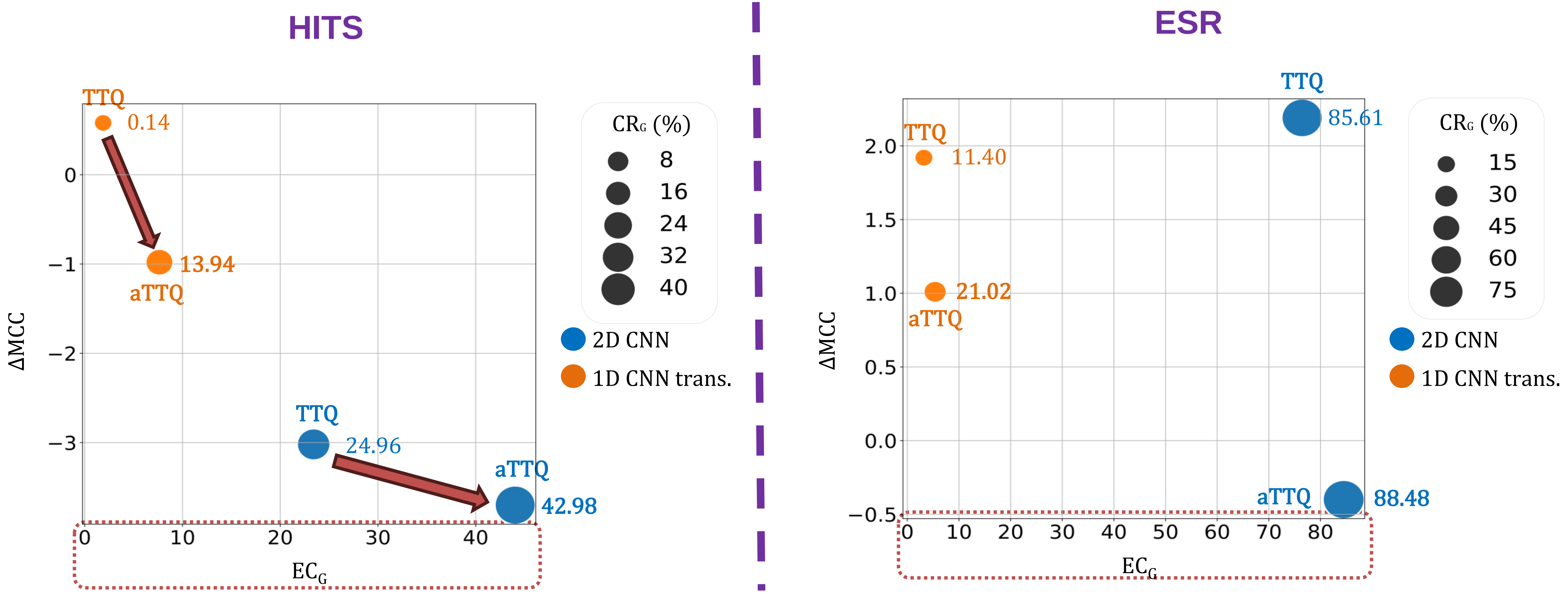
ESR



aTTQ always have higher energy consumption gains compared to TTQ.

Figure – Comparison of aTTQ with FP and TTQ

Experiment: SOTA comparison

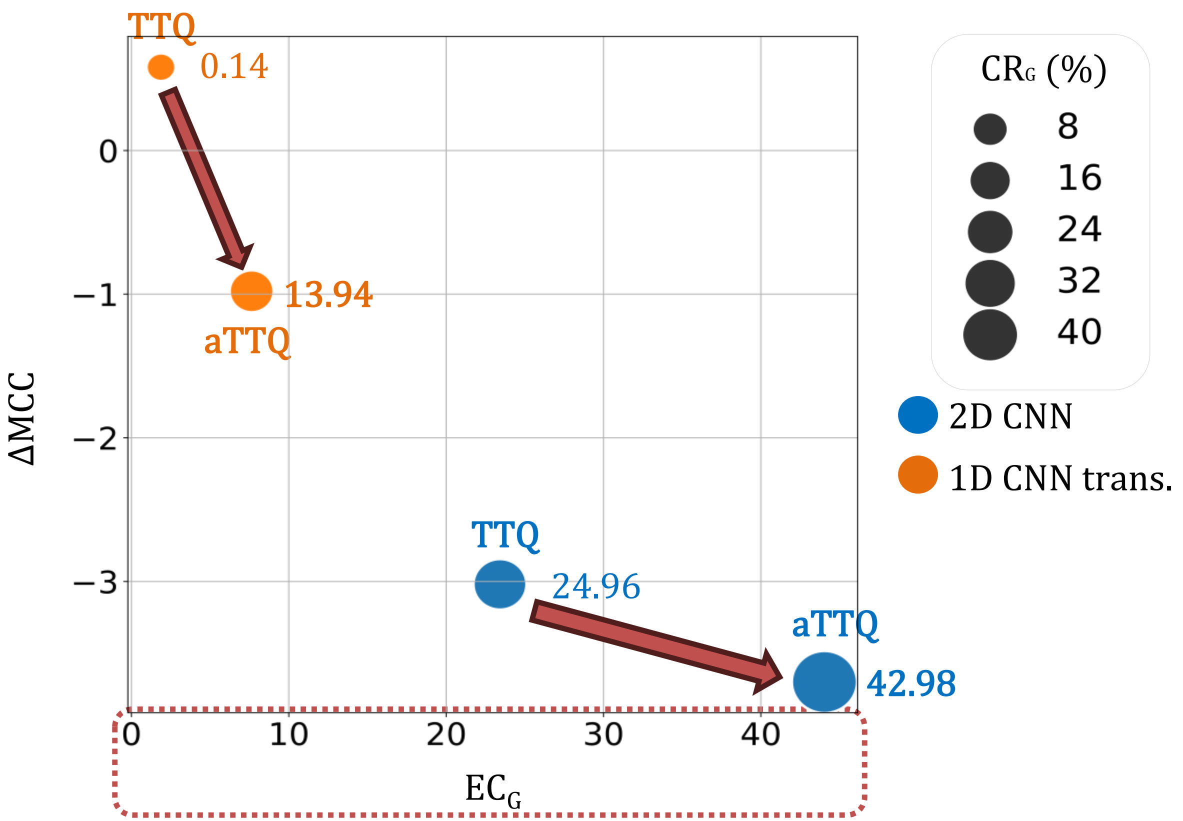


aTTQ always have higher energy consumption gains compared to TTQ.

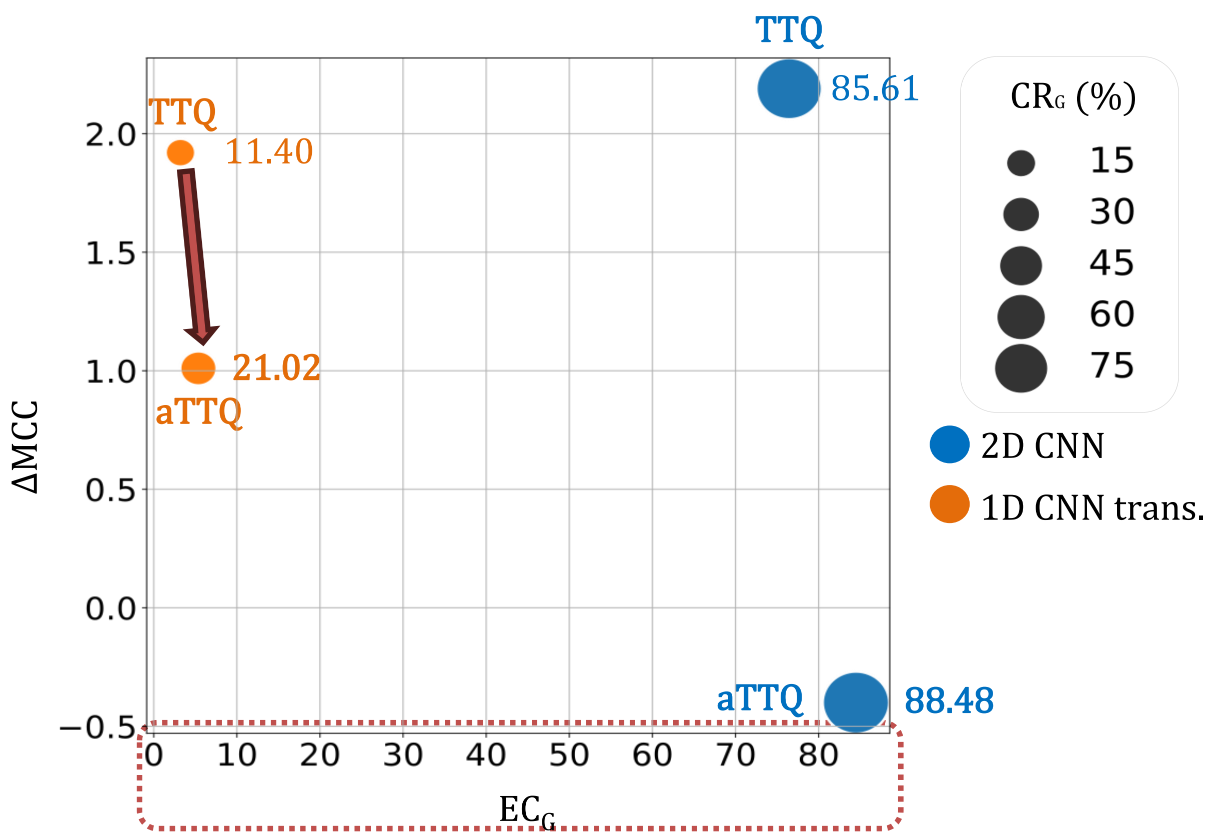
Figure – Comparison of aTTQ with FP and TTQ

Experiment: SOTA comparison

HITS



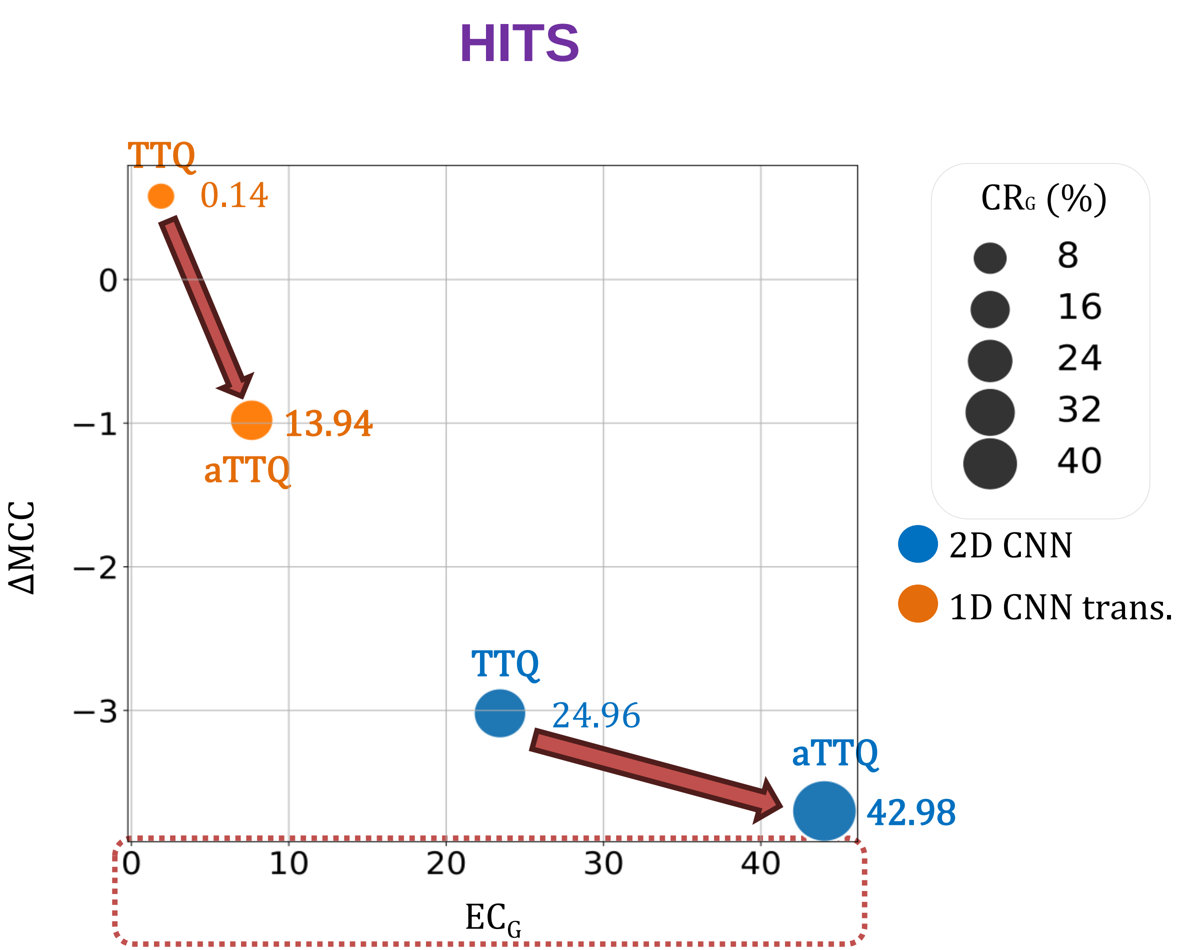
ESR

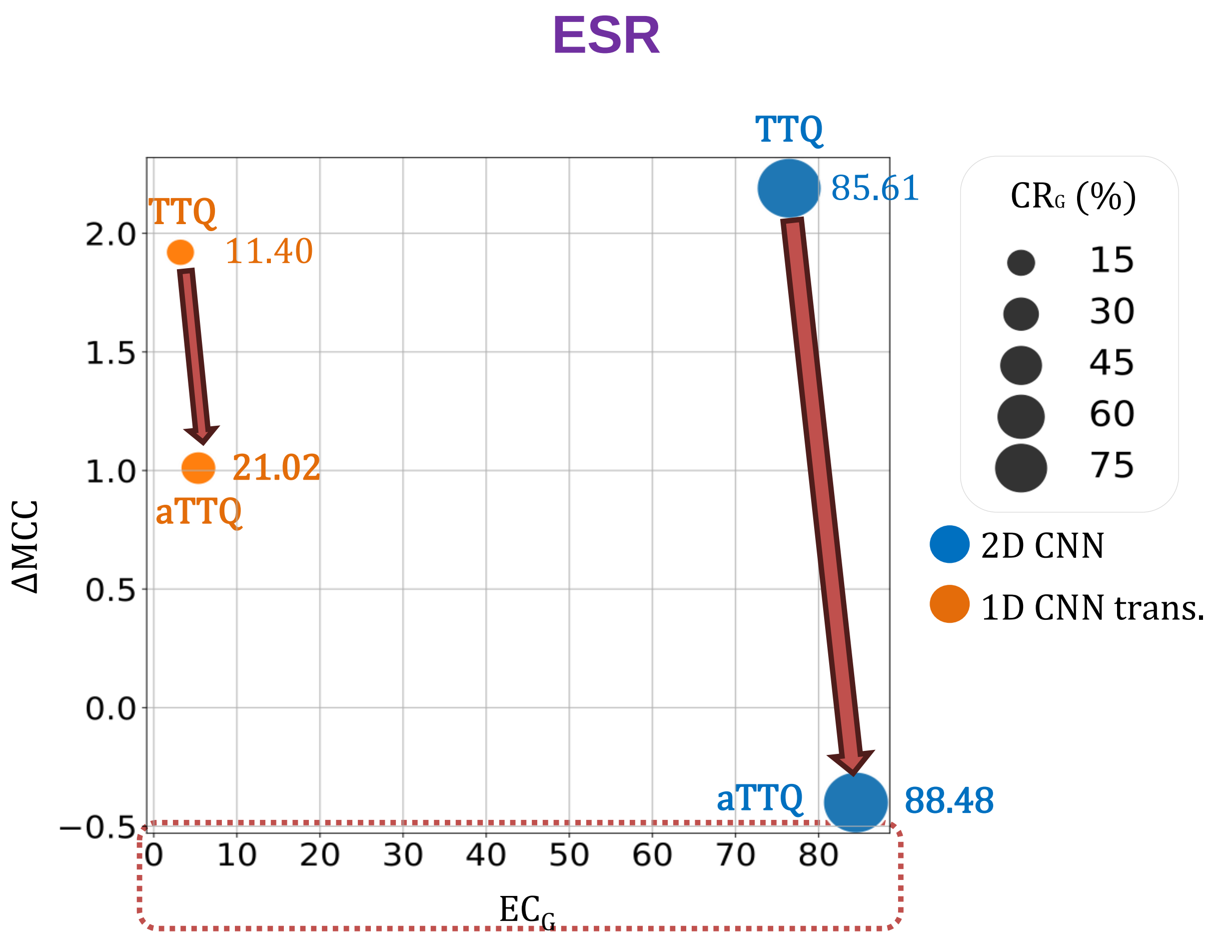


aTTQ always have higher energy consumption gains compared to TTQ.

Figure – Comparison of aTTQ with FP and TTQ

Experiment: SOTA comparison

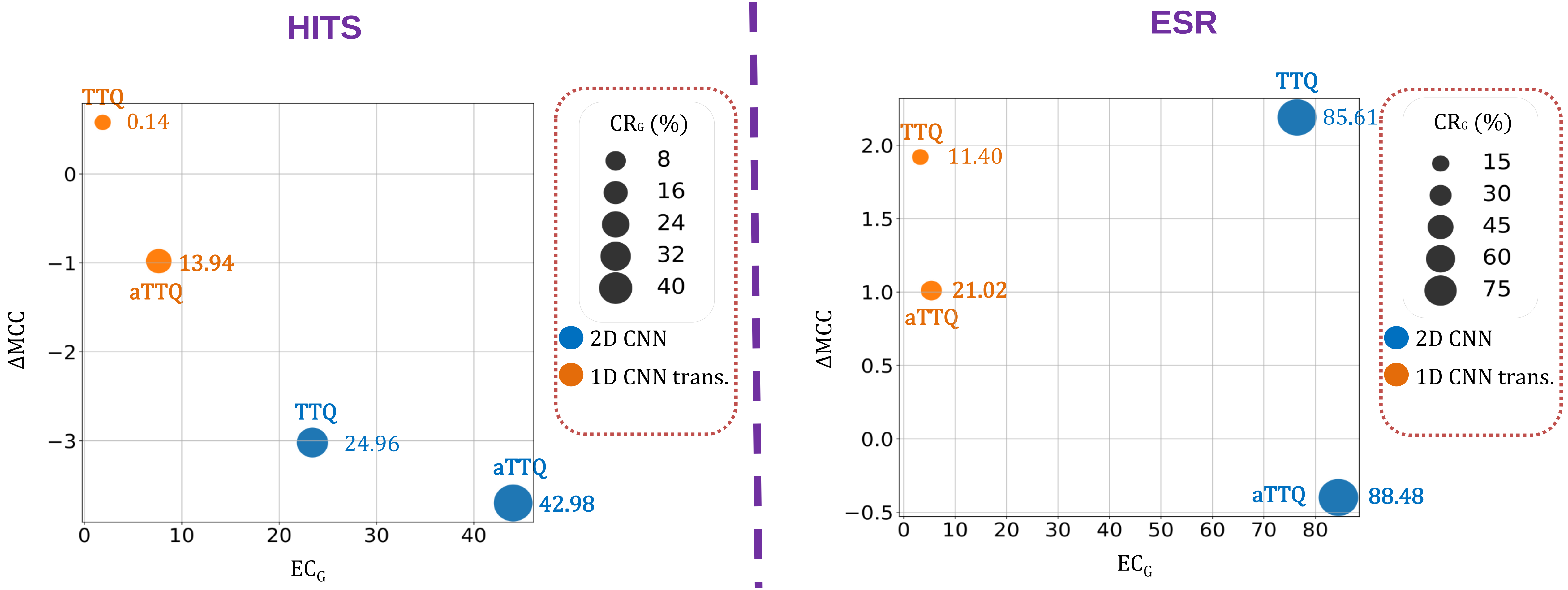




aTTQ always have higher energy consumption gains compared to TTQ.

Figure – Comparison of aTTQ with FP and TTQ

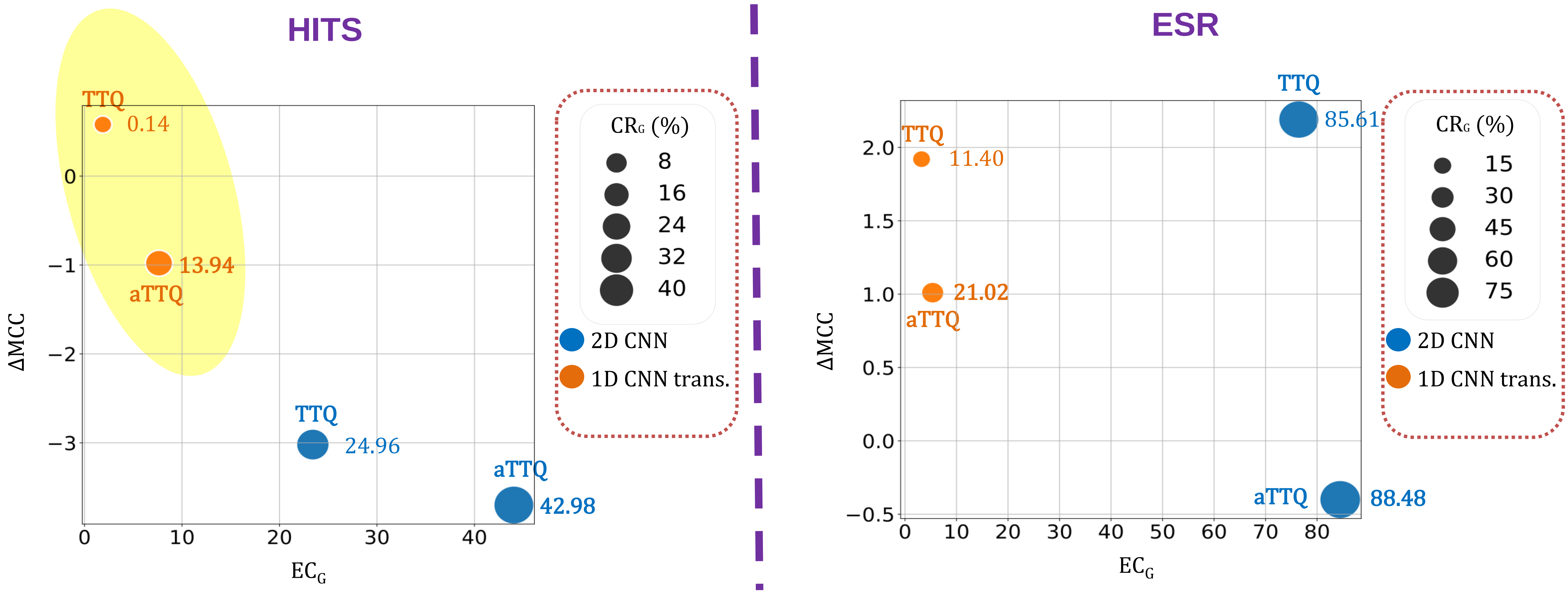
Experiment: SOTA comparison



aTTQ always achieves higher sparsity rates compared to TTQ.

Figure – Comparison of aTTQ with FP and TTQ

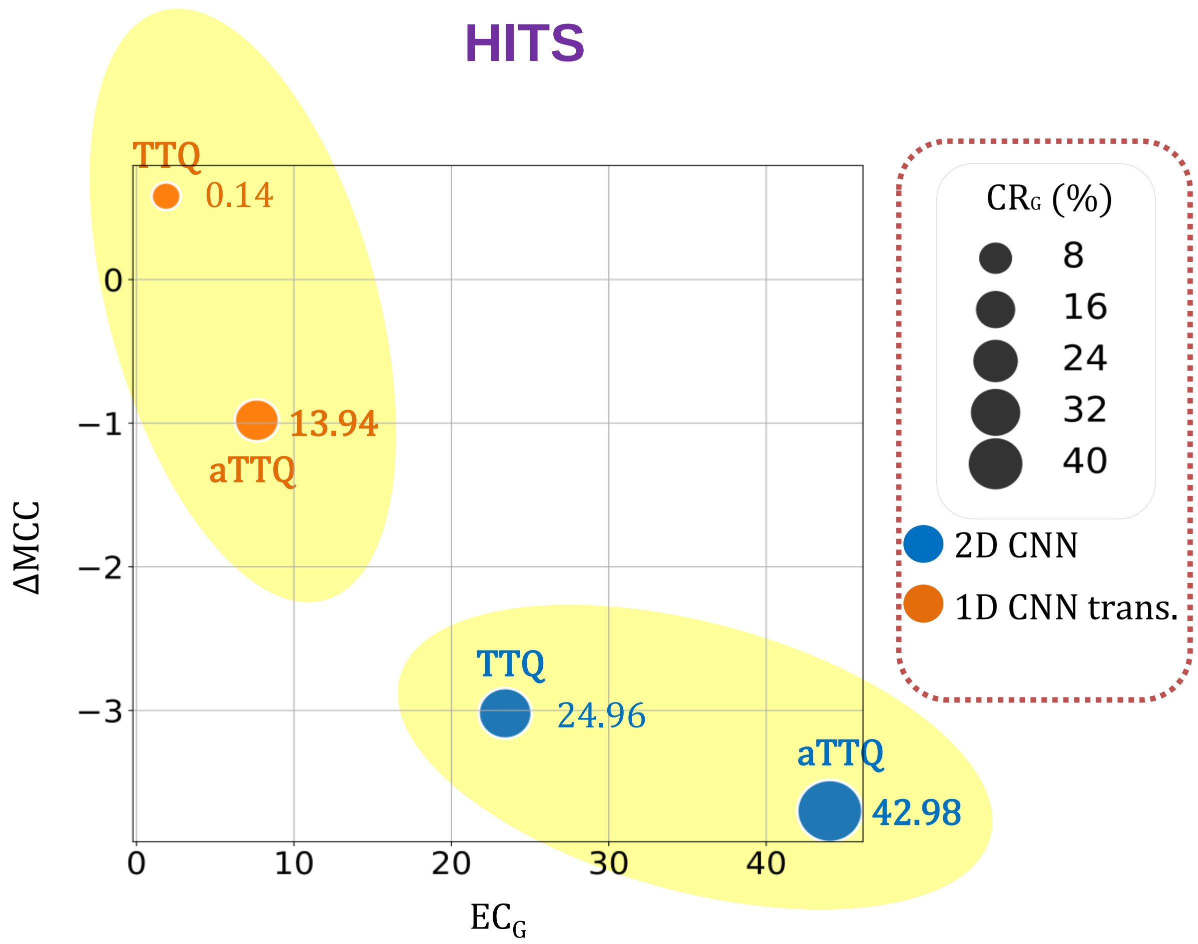
Experiment: SOTA comparison

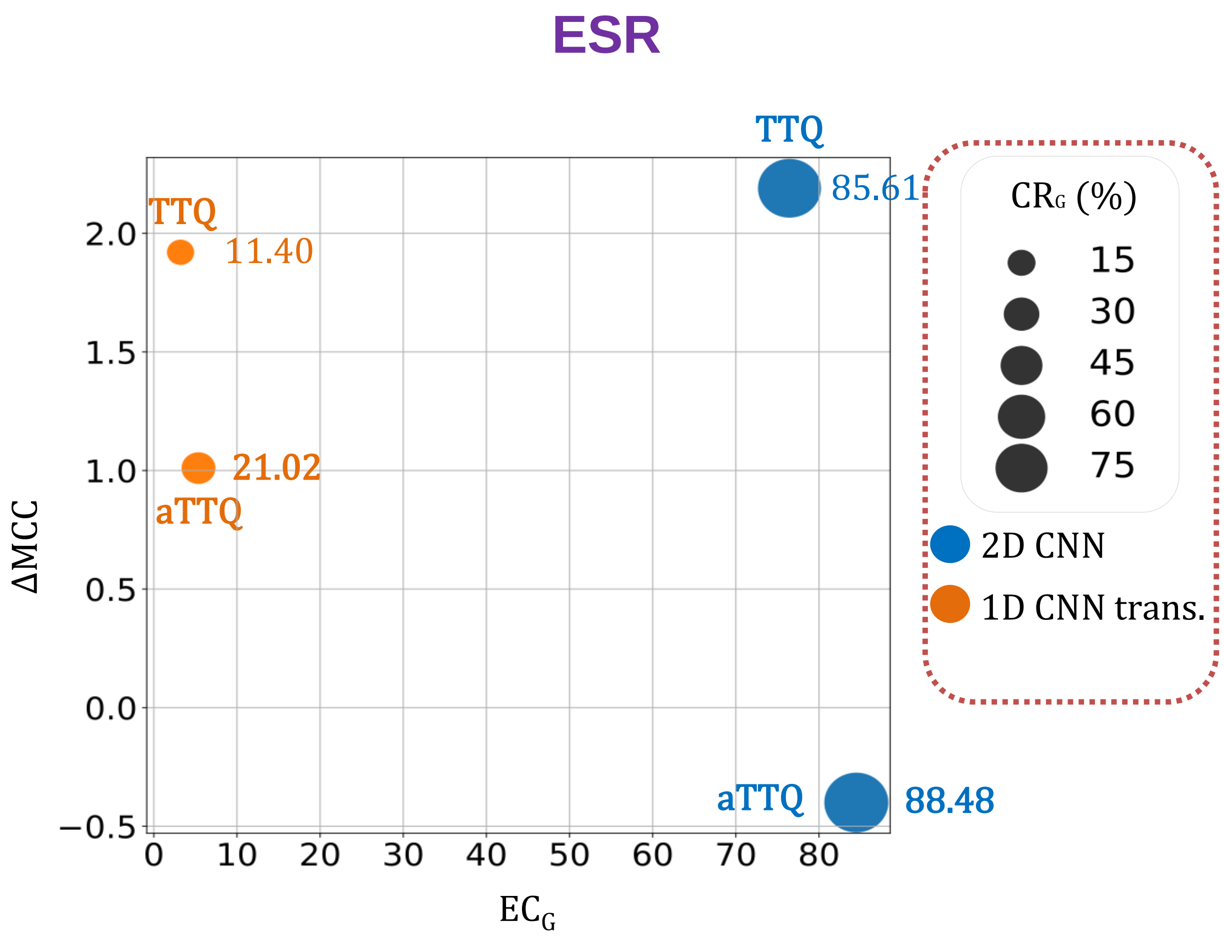


aTTQ always achieves higher sparsity rates compared to TTQ.

Figure – Comparison of aTTQ with FP and TTQ

Experiment: SOTA comparison

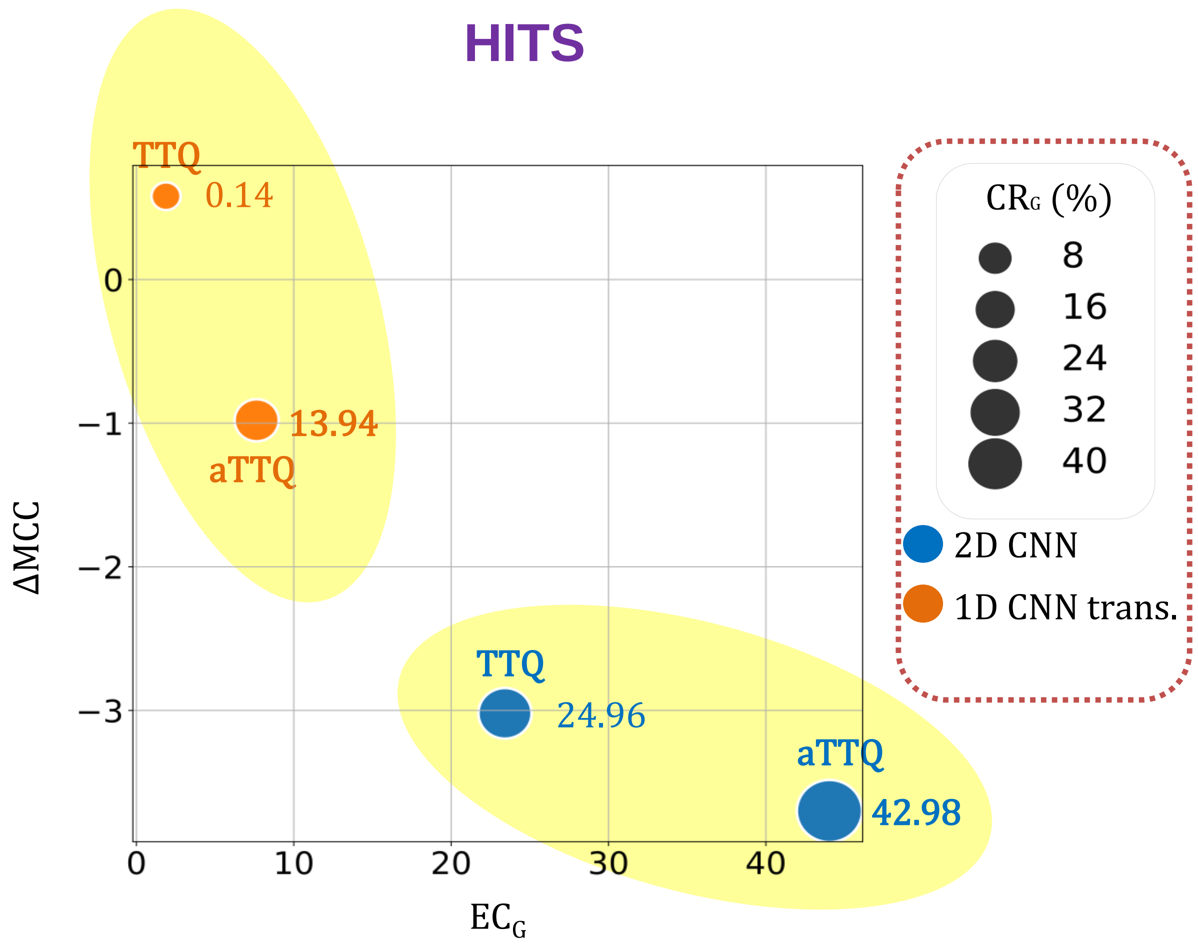


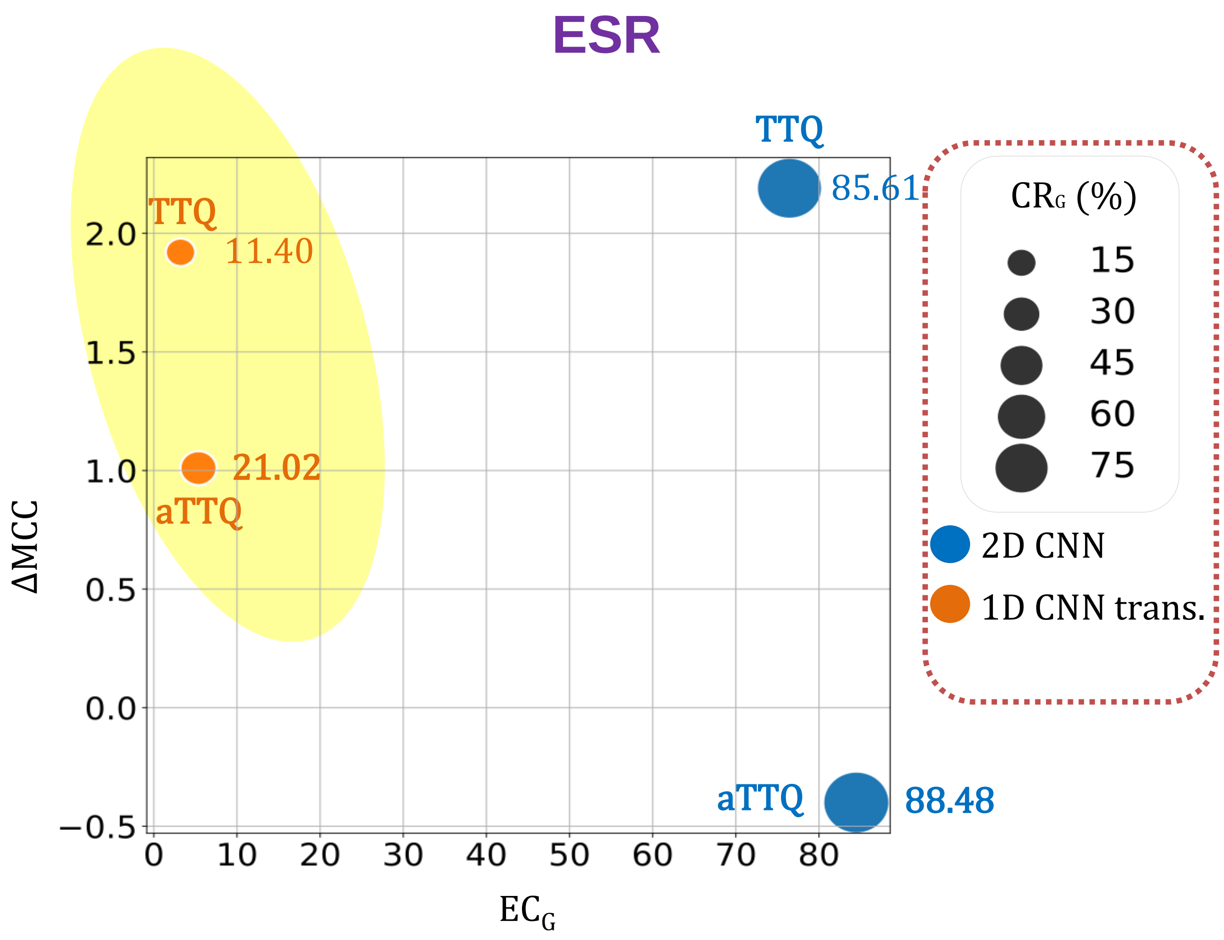


aTTQ always achieves higher sparsity rates compared to TTQ.

Figure – Comparison of aTTQ with FP and TTQ

Experiment: SOTA comparison

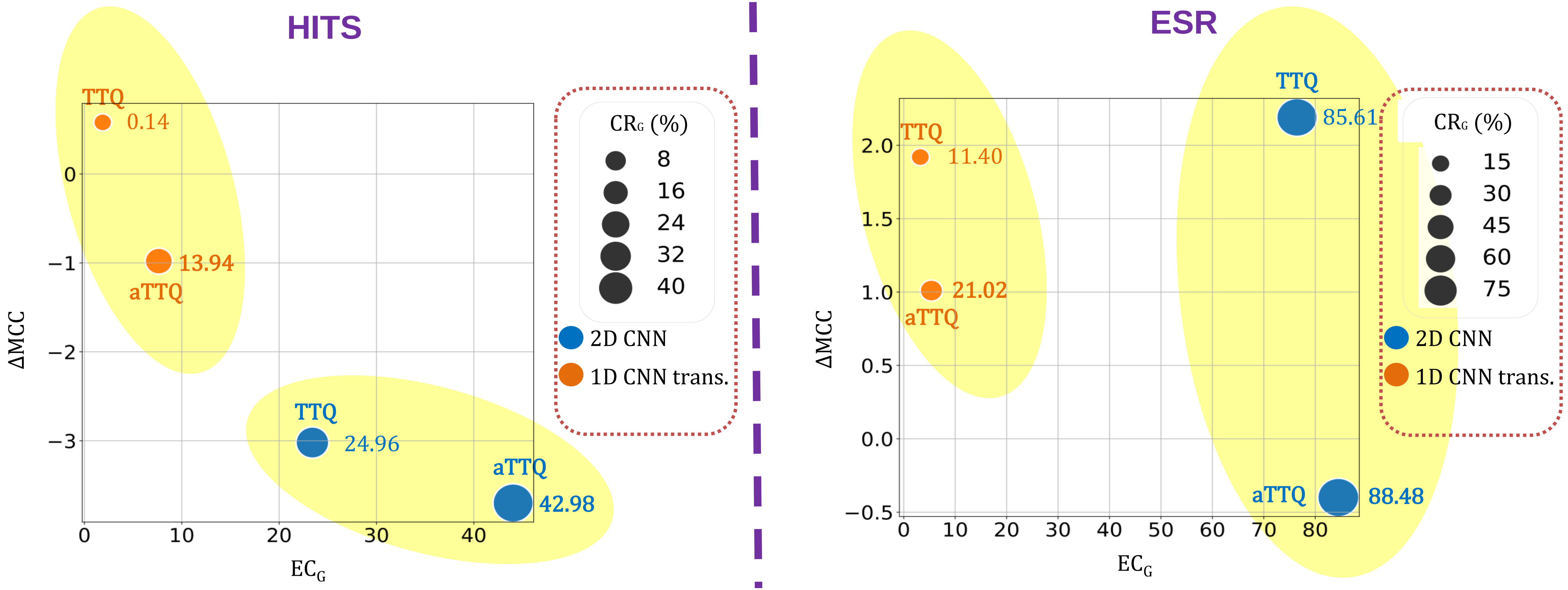




aTTQ always achieves higher sparsity rates compared to TTQ.

Figure – Comparison of aTTQ with FP and TTQ

Experiment: SOTA comparison

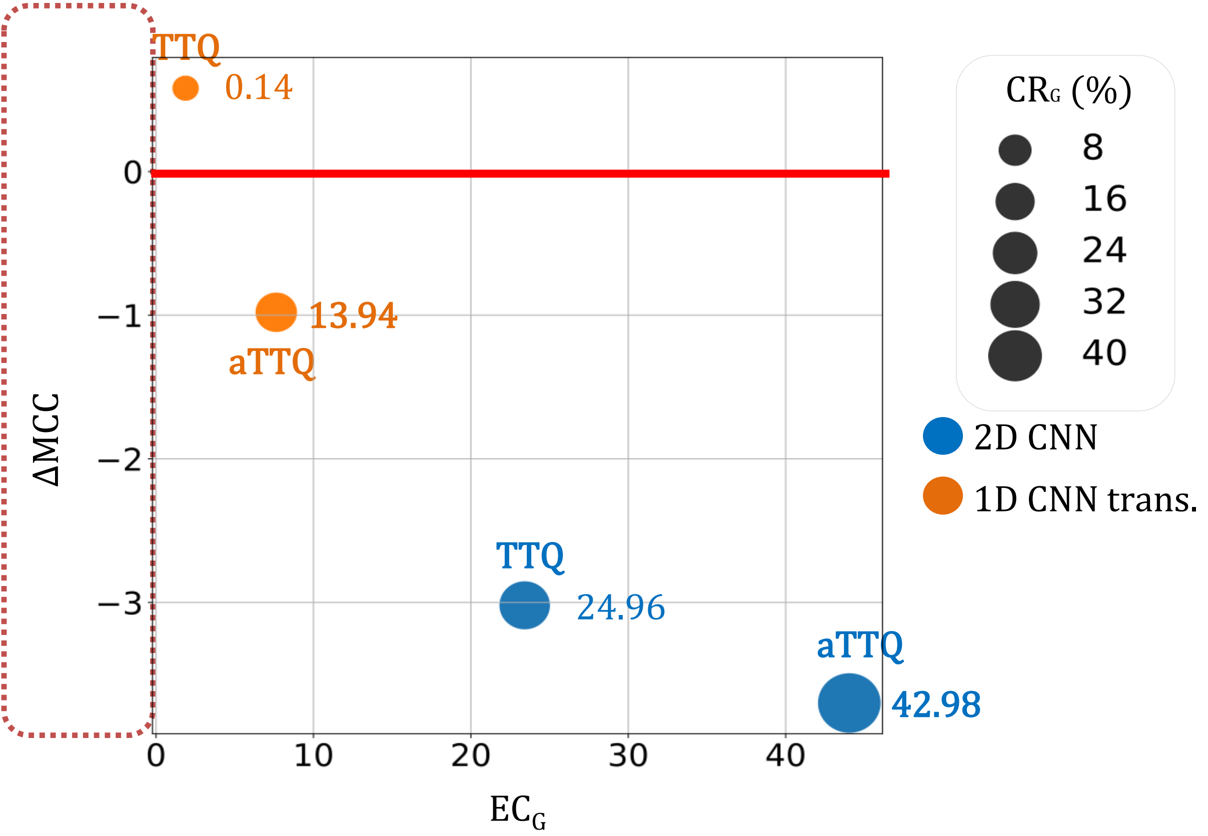


aTTQ always achieves higher sparsity rates compared to TTQ.

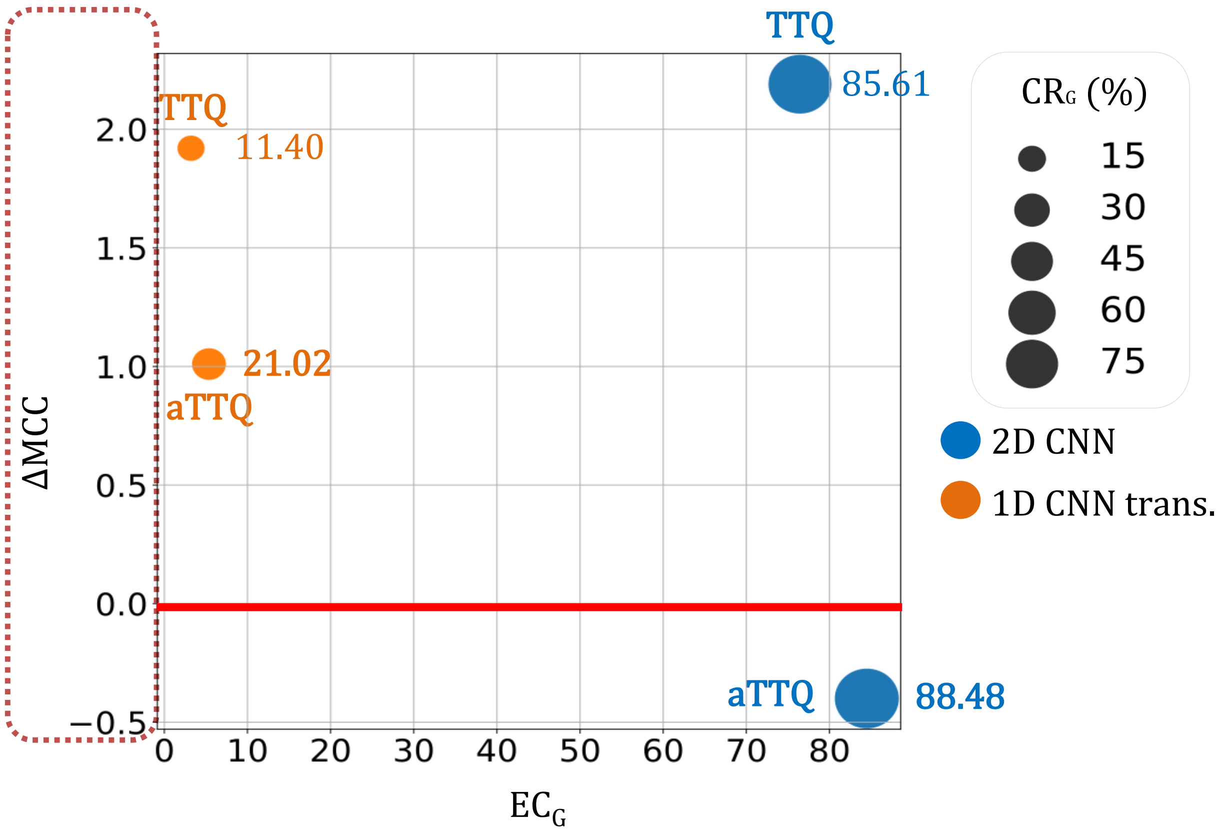
Figure – Comparison of aTTQ with FP and TTQ

Experiment: SOTA comparison

HITS



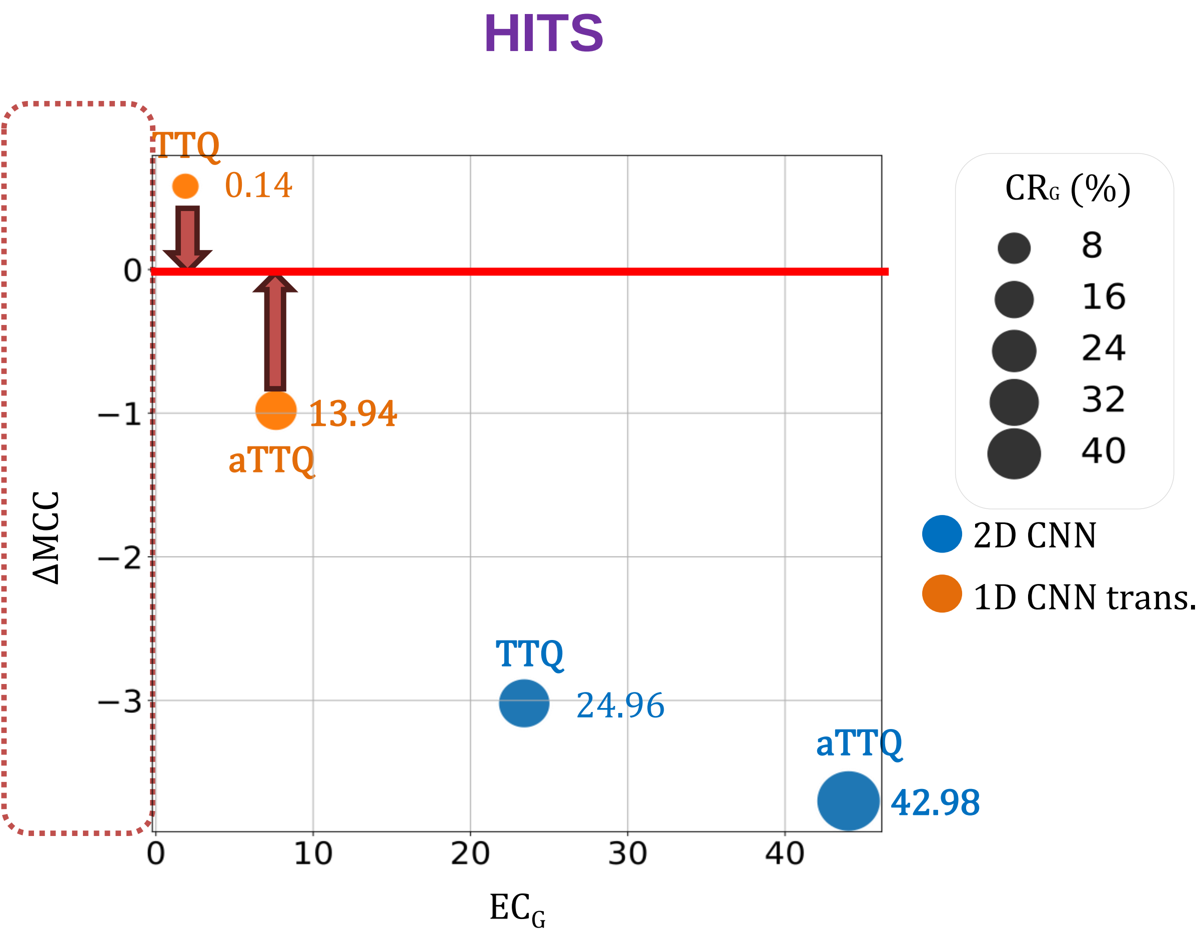
ESR

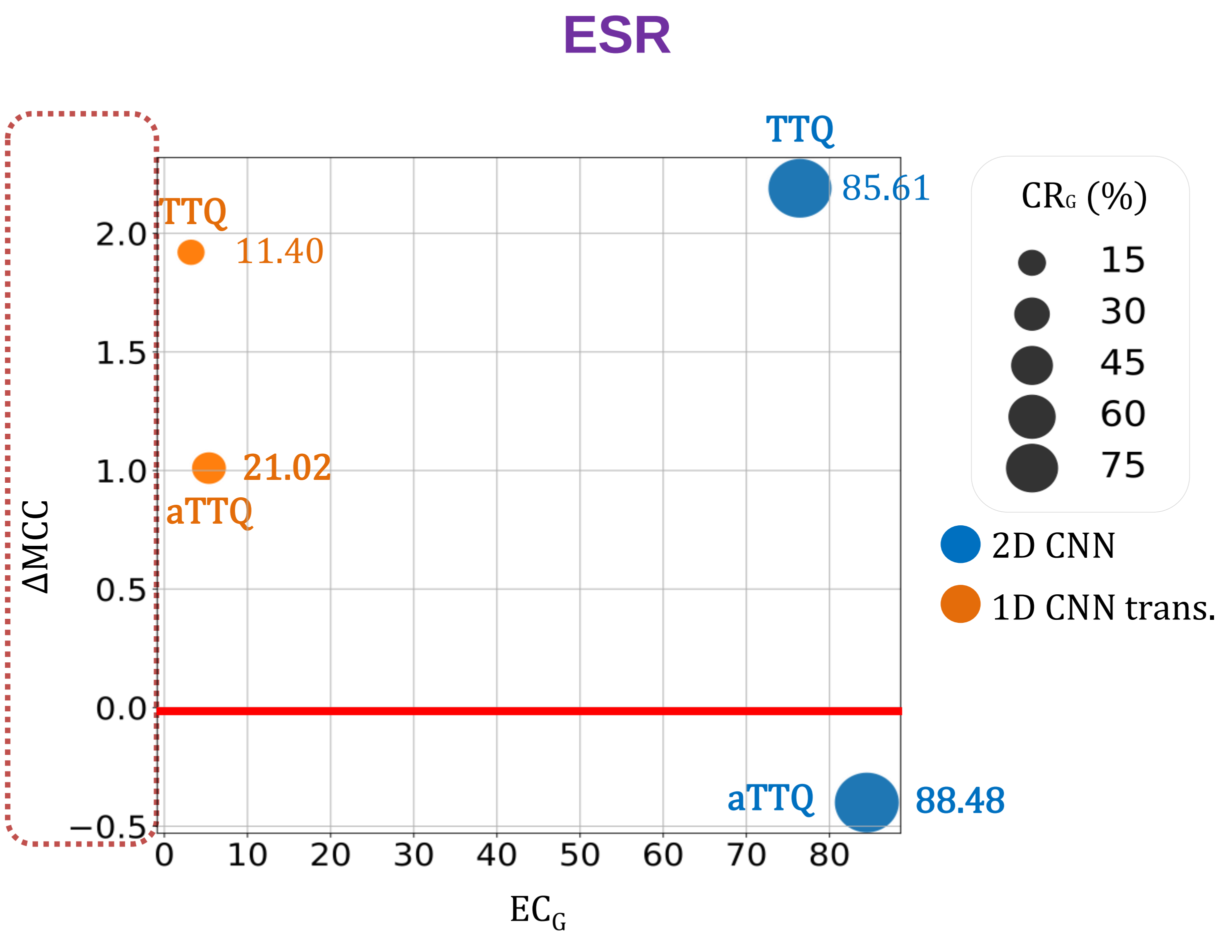


Both aTTQ and TTQ perform similarly than the FP model in terms of classification

Figure – Comparison of aTTQ with FP and TTQ

Experiment: SOTA comparison



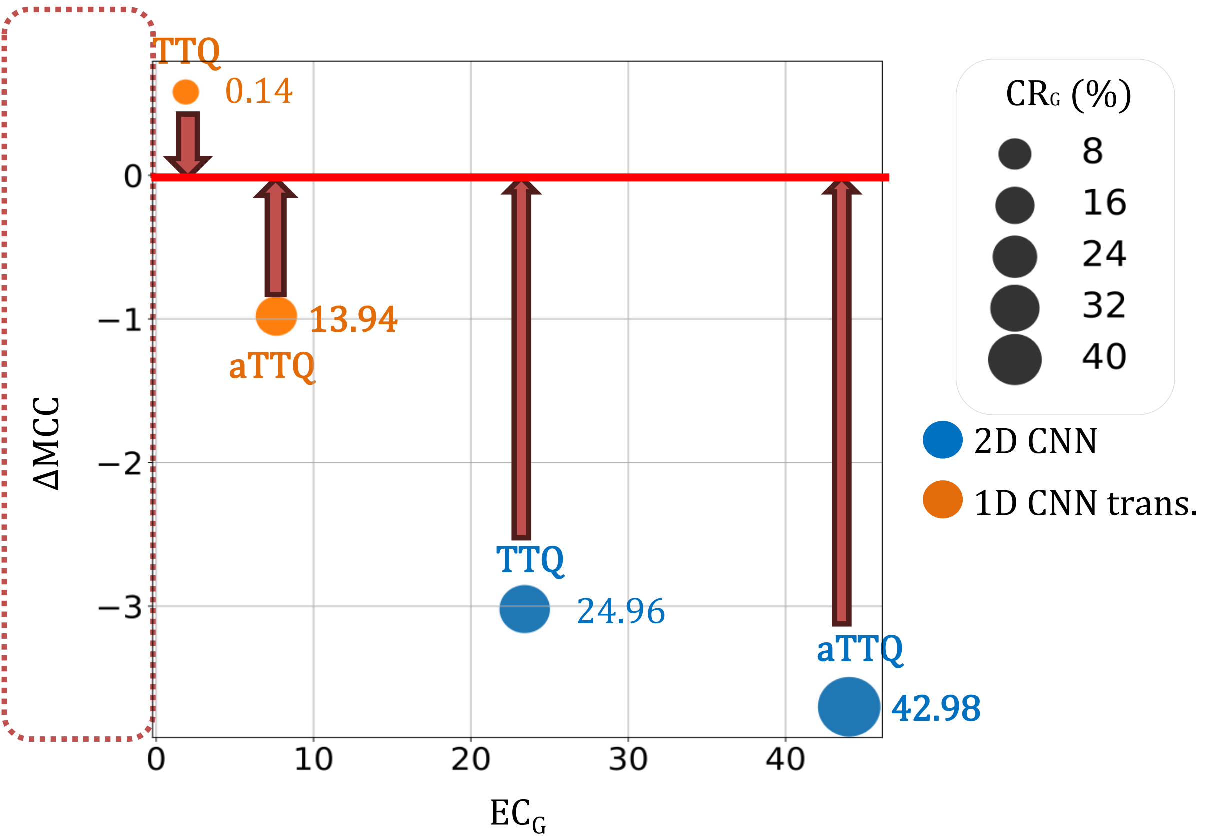


Both aTTQ and TTQ perform similarly than the FP model in terms of classification

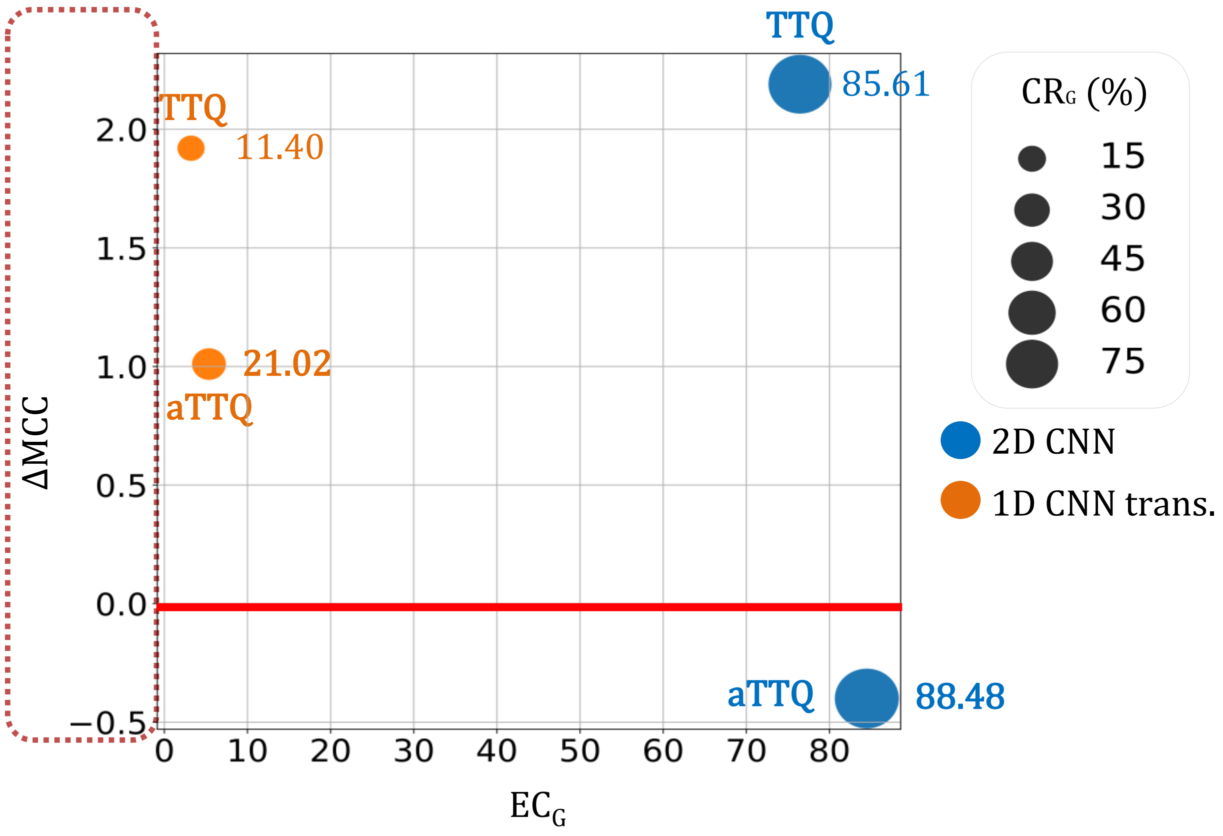
Figure – Comparison of aTTQ with FP and TTQ

Experiment: SOTA comparison

HITS



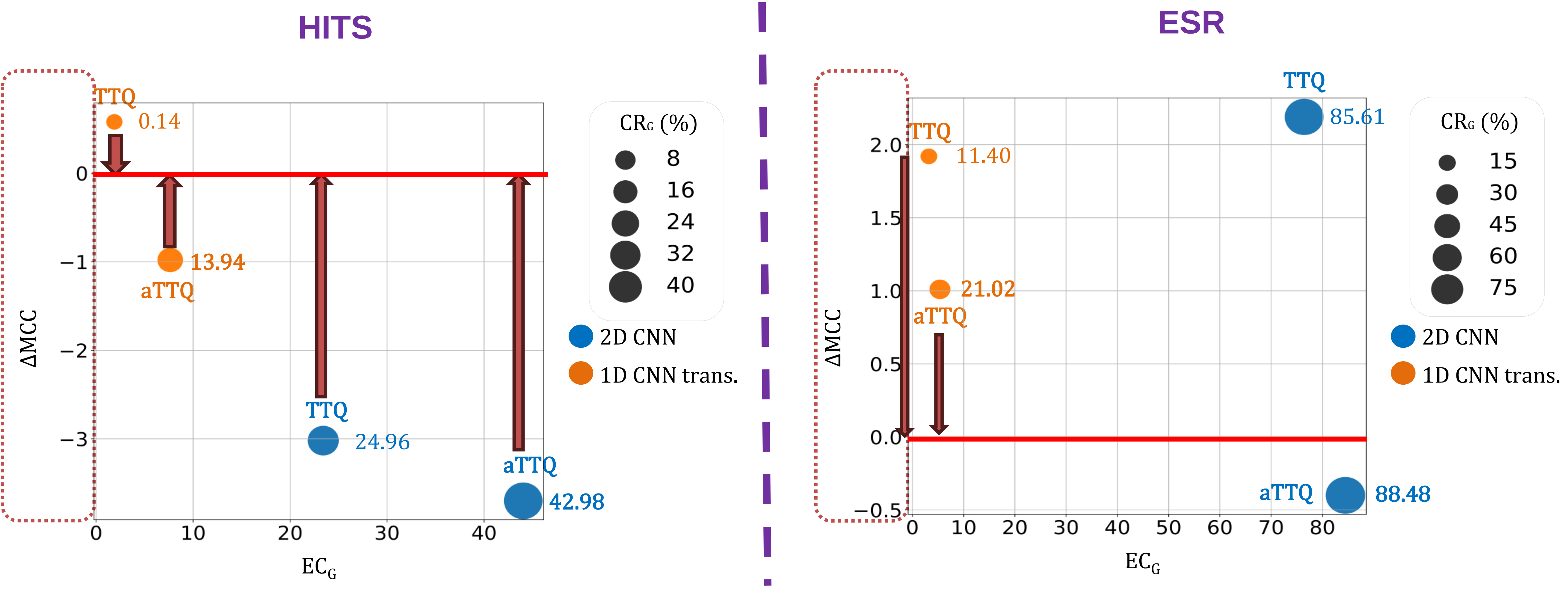
ESR



Both aTTQ and TTQ perform similarly than the FP model in terms of classification

Figure – Comparison of aTTQ with FP and TTQ

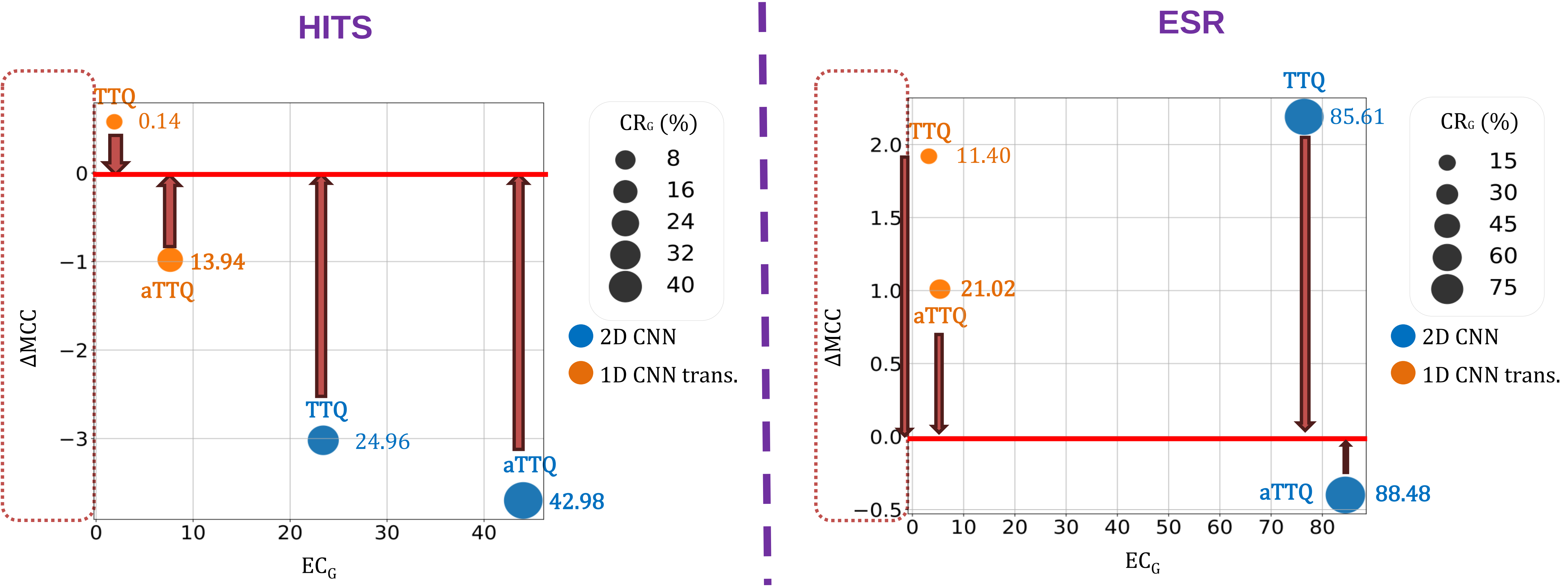
Experiment: SOTA comparison



Both aTTQ and TTQ perform similarly than the FP model in terms of classification

Figure – Comparison of aTTQ with FP and TTQ

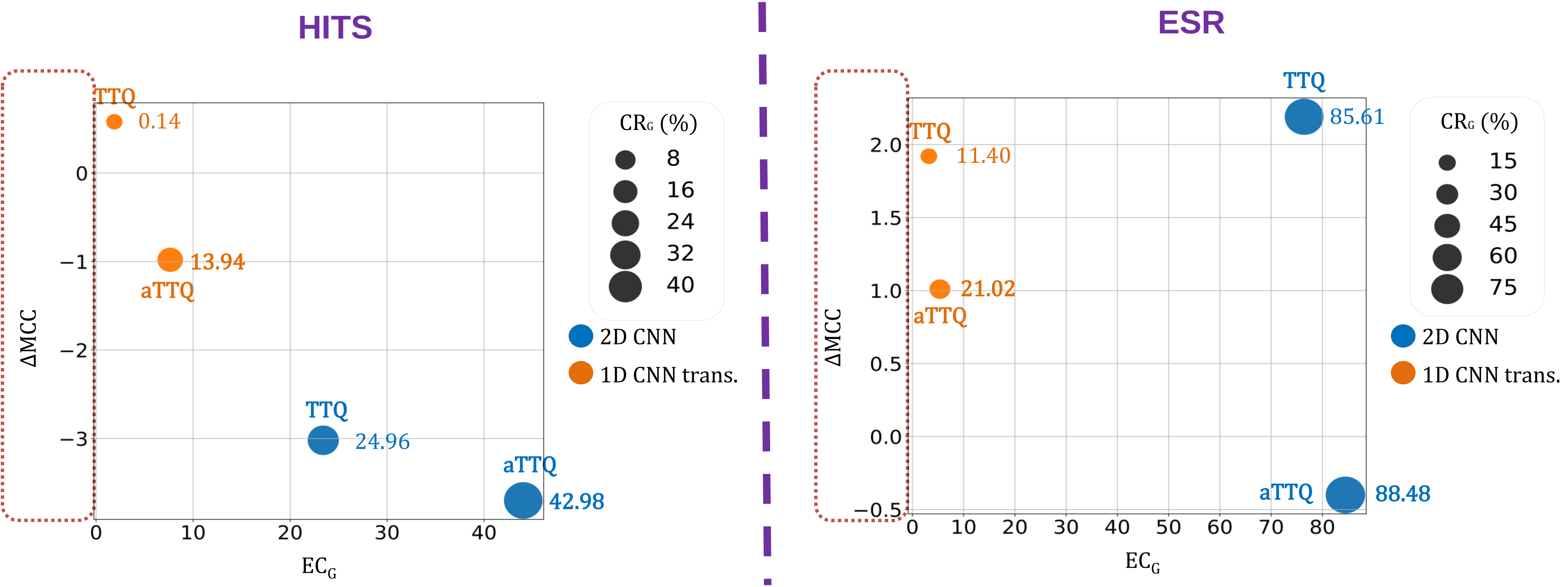
Experiment: SOTA comparison



Both aTTQ and TTQ perform similarly than the FP model in terms of classification

Figure – Comparison of aTTQ with FP and TTQ

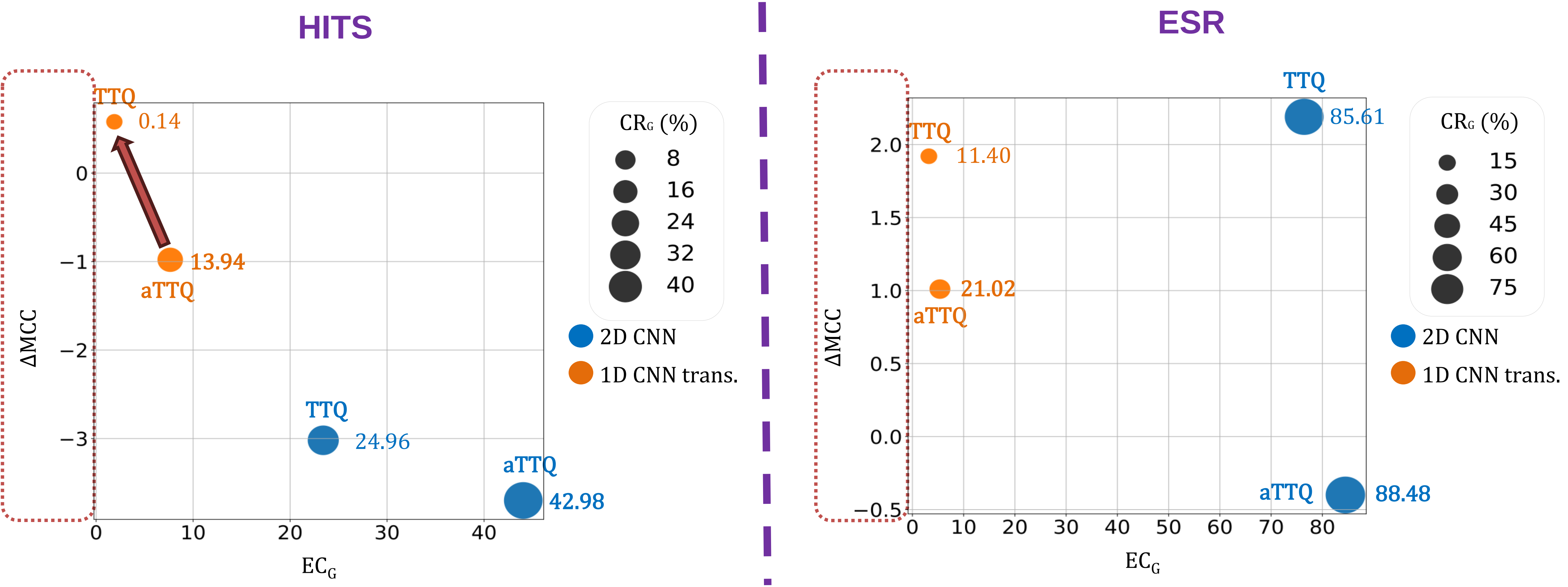
Experiment: SOTA comparison



TTQ tend to have slightly higher classification performances than aTTQ

Figure – Comparison of aTTQ with FP and TTQ

Experiment: SOTA comparison

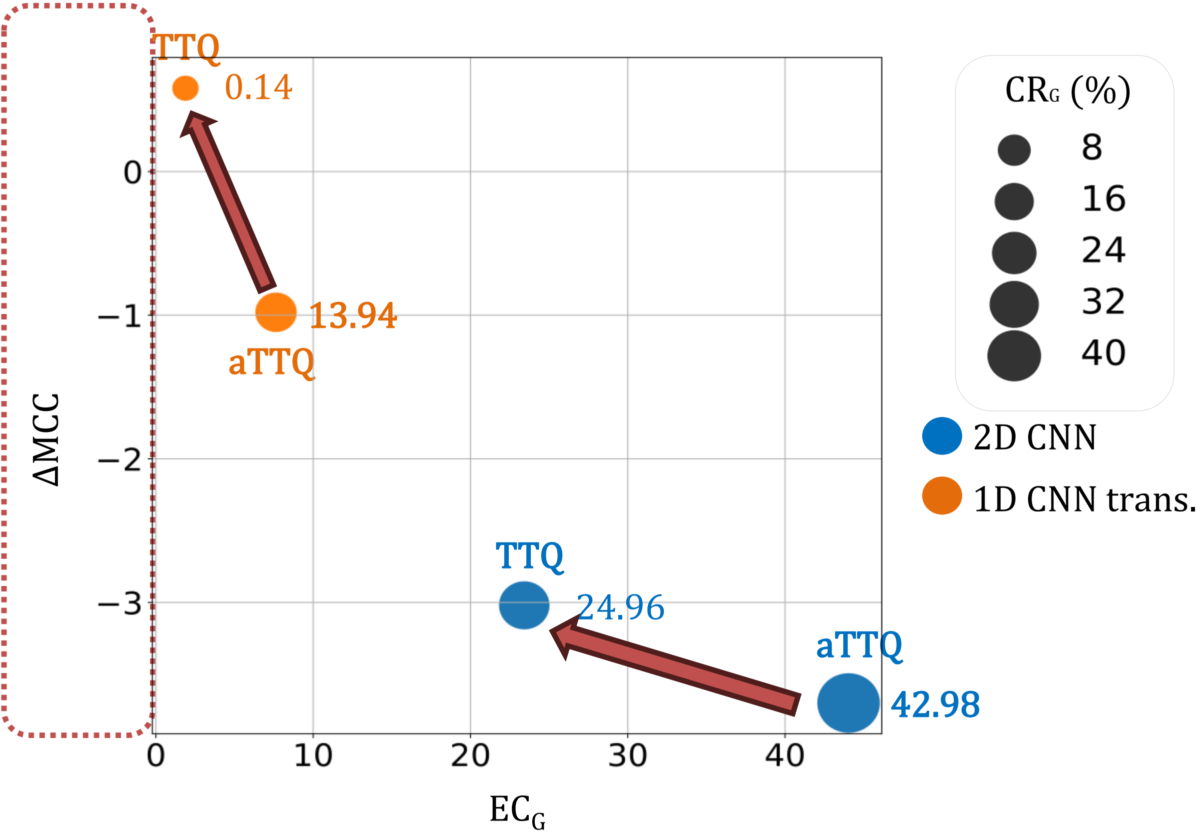


TTQ tend to have slightly higher classification performances than aTTQ

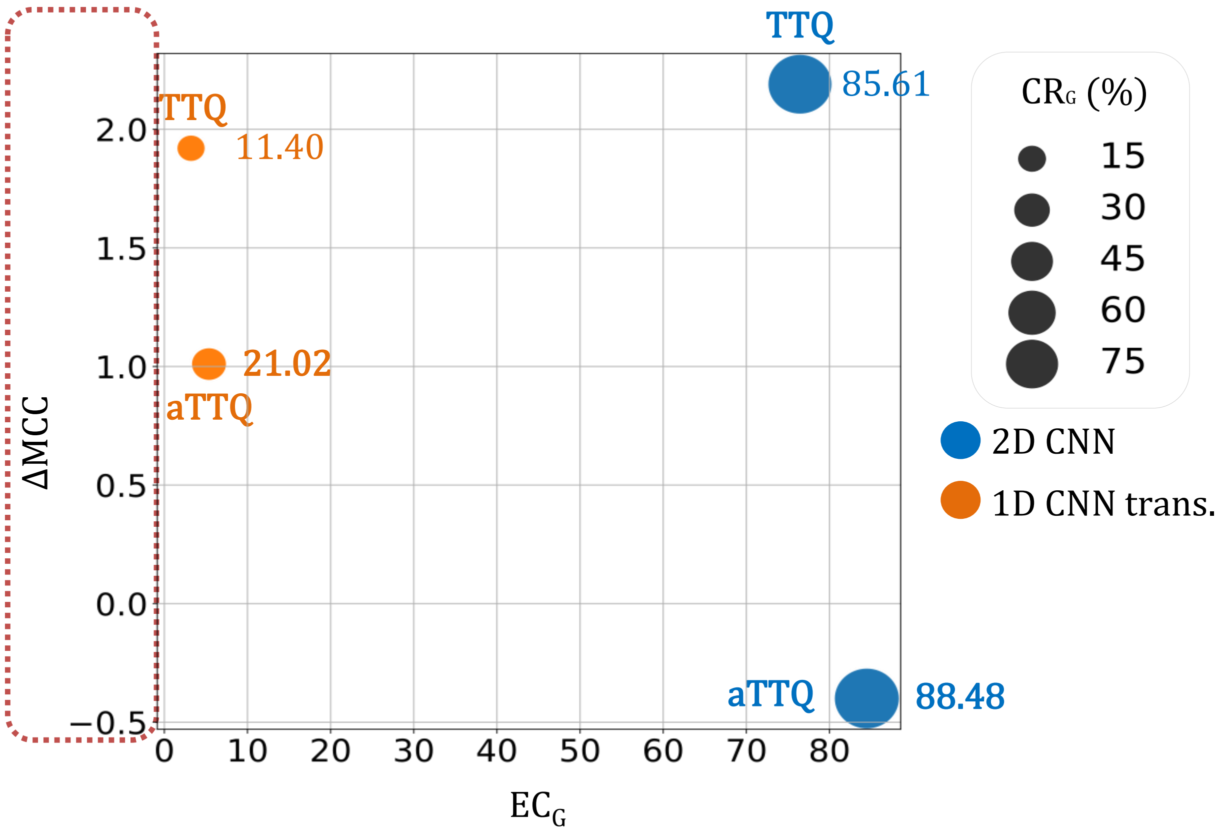
Figure – Comparison of aTTQ with FP and TTQ

Experiment: SOTA comparison

HITS



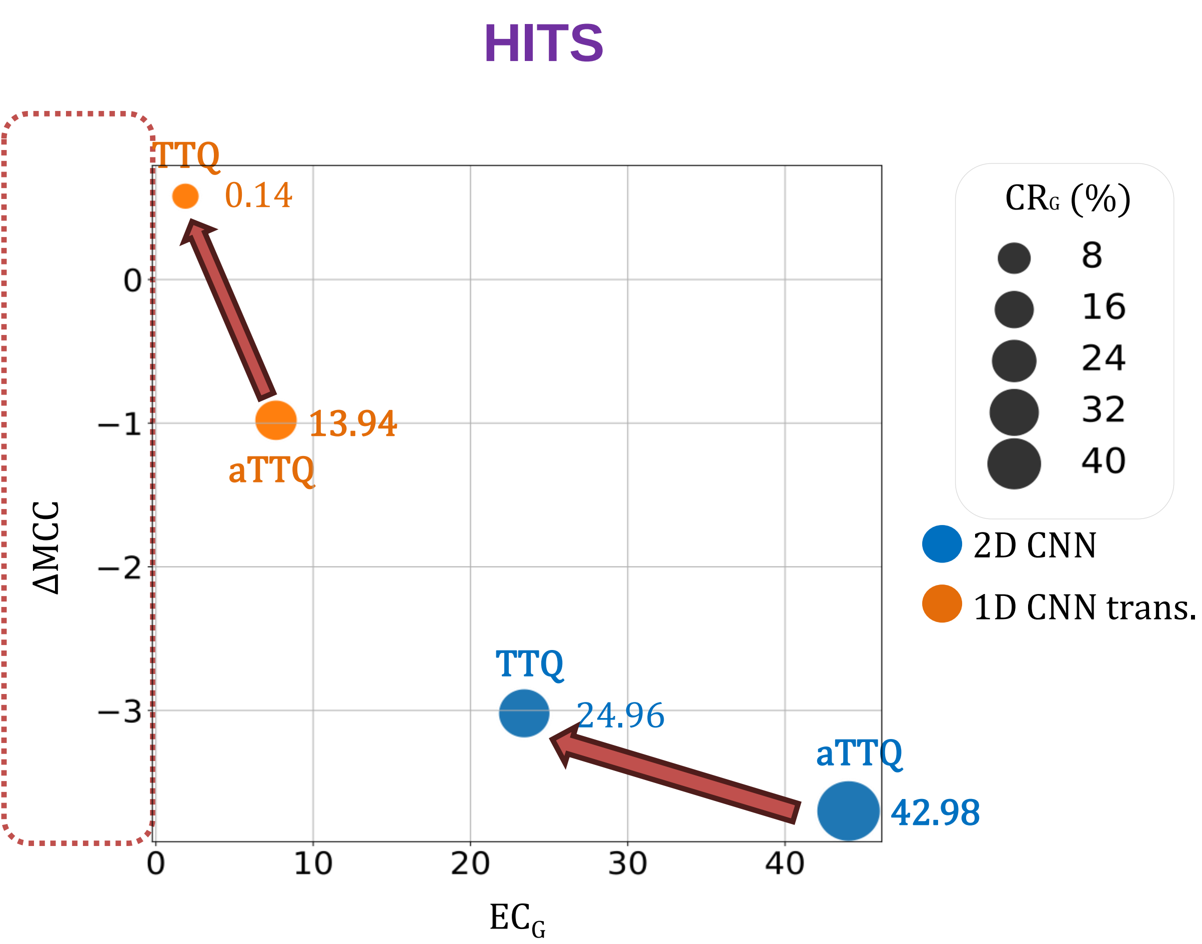
ESR

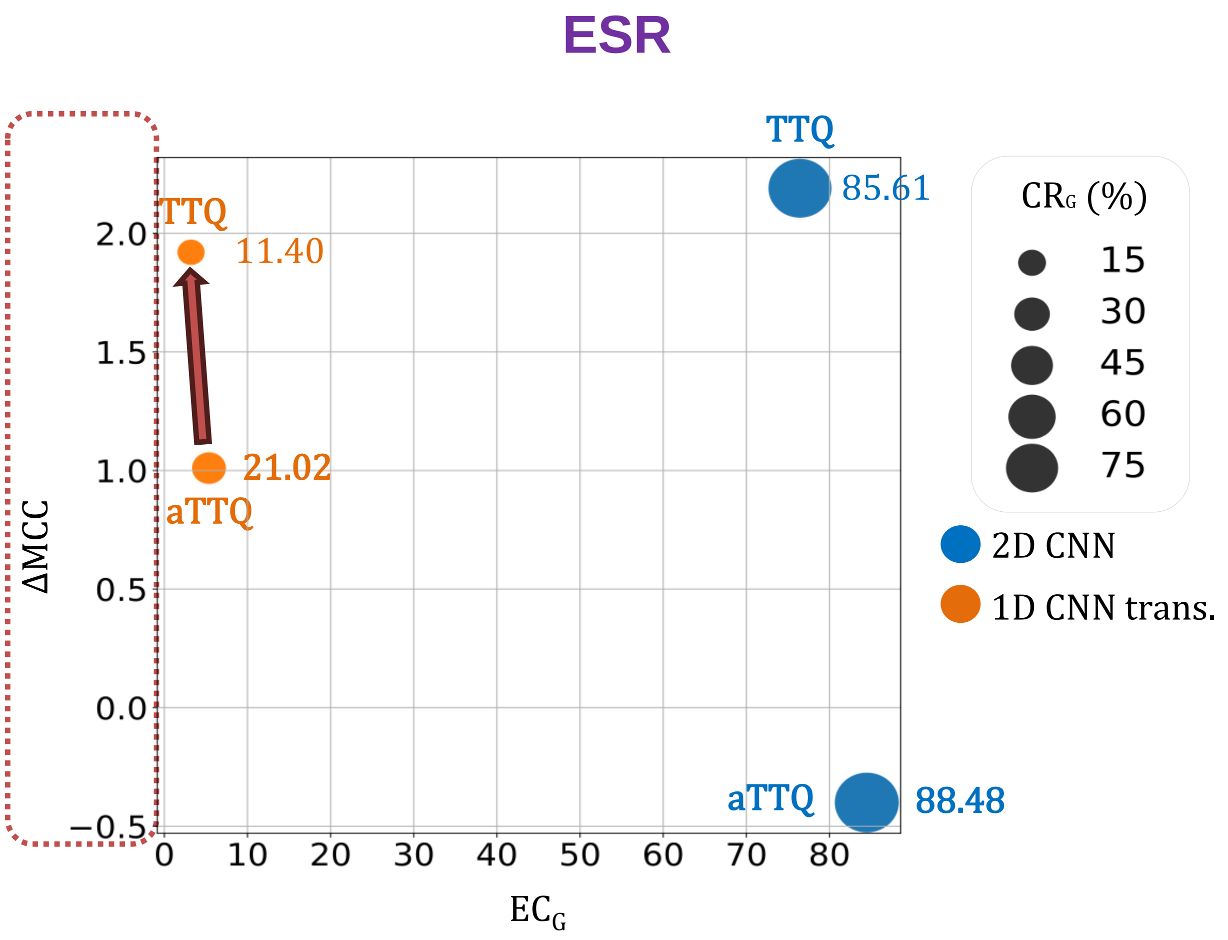


TTQ tend to have slightly higher classification performances than aTTQ

Figure – Comparison of aTTQ with FP and TTQ

Experiment: SOTA comparison

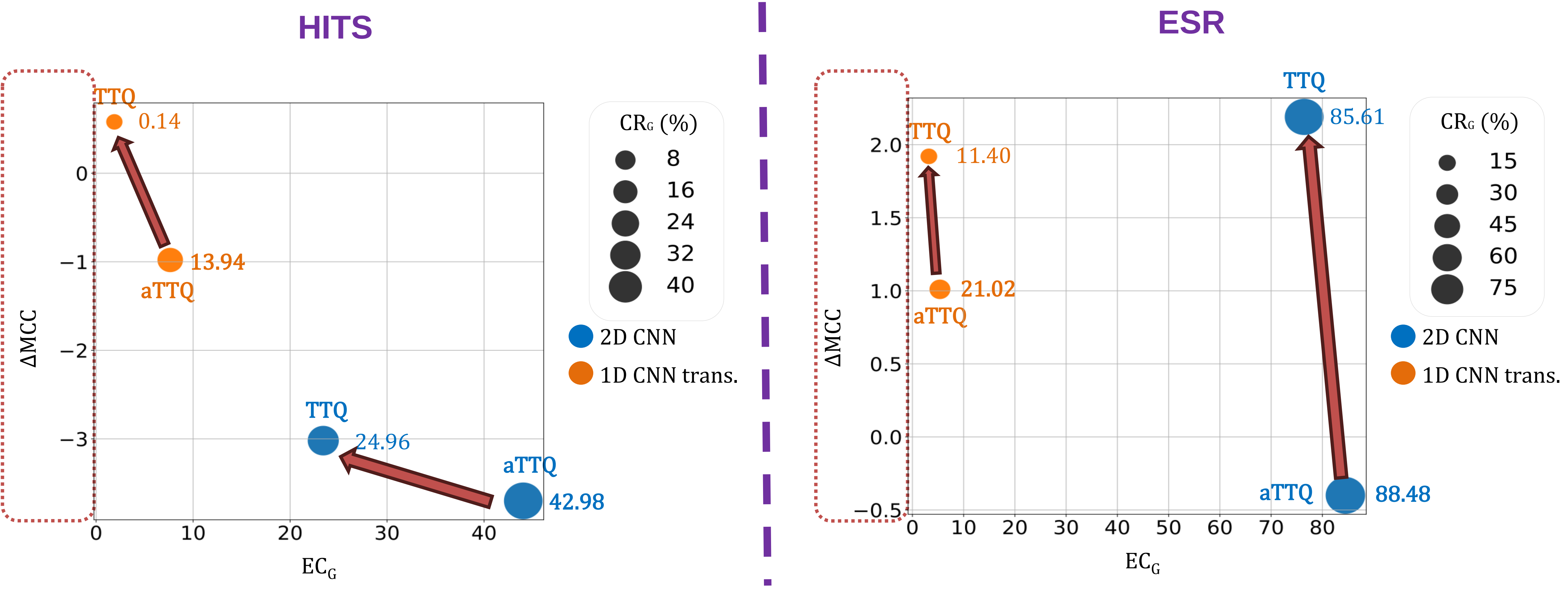




TTQ tend to have slightly higher classification performances than aTTQ

Figure – Comparison of aTTQ with FP and TTQ

Experiment: SOTA comparison



TTQ tend to have slightly higher classification performances than aTTQ

Figure – Comparison of aTTQ with FP and TTQ

Experiment: SOTA comparison

Dataset	Model	Quant. method	CR_G^T ↑	CR_G^Q ↑	$SRQW$ ↑	$\mathbf{EC_G^T}$ ↑	MCC ↑	Δ MCC ↑
HITS	2D CNN	FP	-	-	-	-	89.84 ± 3.09	-
		DoReFa [21]	**89.18** ± **0**	**96.87** ± **0**	-	3.54 ± 0	85.05 ± 5.96	−4.79
		TTQ [16]	24.96 ± 2.25	27.12 ± 2.44	28.96 ± 2.12	*23.42 ± 1.30*	**86.82** ± **2.29**	**−3.02**
		aTTQ	*42.98 ± 0.23*	*46.69 ± 0.25*	**45.95** ± **0.21**	**44.04** ± **0.19**	*86.14 ± 3.37*	*−3.70*
	1D CNN-trans.	FP	-	-	-	-	82.64 ± 1.77	-
		DoReFa [21]	**14.50** ± **0**	**96.87** ± **0**	-	0.37 ± 0.03	**84.07** ± **3.11**	**+1.43**
		TTQ [16]	0.14 ± 0.04	0.91 ± 0.27	6.75 ± 0.26	*1.88 ± 0.03*	*83.22 ± 2.36*	*+0.58*
		aTTQ	*13.94 ± 0.02*	*93.17 ± 0.16*	**93.53** ± **0.15**	**7.64** ± **0.11**	81.66 ± 4.17	−0.98
ESR	2D CNN	FP	-	-	-	-	92.81 ± 3.53	-
		DoReFa [21]	**96.40** ± **0**	**96.87** ± **0**	-	29.90 ± 0	*94.12 ± 0.87*	*+1.31*
		TTQ [16]	85.61 ± 1.37	86.03 ± 1.37	86.59 ± 1.29	*76.45 ± 1.13*	**95.00** ± **1.11**	**+2.19**
		aTTQ	*88.48 ± 0.44*	*88.91 ± 0.45*	**89.30** ± **0.42**	**84.49** ± **0.33**	92.41 ± 2.22	−0.40
	1D CNN-trans.	FP	-	-	-	-	94.33 ± 1.51	-
		DoReFa [21]	**23.46** ± **0**	**96.86** ± **0**	-	0.90 ± 0	**96.79** ± **0.55**	**+2.46**
		TTQ [16]	11.40 ± 2.61	47.07 ± 10.79	50.22 ± 10.16	*3.21 ± 0.66*	*96.25 ± 0.79*	*+1.92*
		aTTQ	*21.02 ± 0.15*	*86.78 ± 0.63*	**87.59** ± **0.59**	**5.37** ± **0.04**	95.34 ± 0.79	+1.01
MNIST	2D MNIST CNN	FP	-	-	-	-	94.39 ± 0.46	-
		DoReFa [21]	**51.67** ± **0**	**96.84** ± **0**	-	*3.28 ± 0*	87.03 ± 7.14	−7.36
		TTQ [16]	13.86 ± 2.33	25.97 ± 4.37	30.40 ± 4.12	2.58 ± 0.35	*92.09 ± 0.89*	*−2.30*
		aTTQ	*28.98 ± 1.26*	*54.32 ± 2.36*	**57.08** ± **2.22**	**4.97** ± **0.22**	**93.62** ± **0.96**	**−0.77**

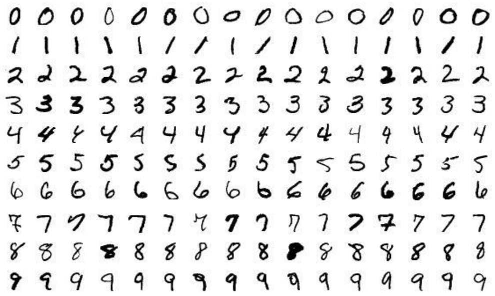
Table – Comparison of **aTTQ** with other quantization methods

Experiment: influence of normalization

Objective:

- Study the influence of normalization on aTTQ.

Datasets:

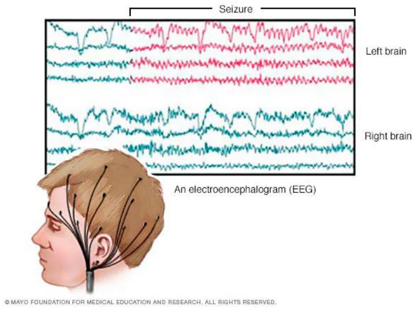


MNIST subset:

- 28x28 images.
- 20 000 samples.
- Ten classes.

HITS:

- TCD Data.
- 1 545 samples.
- Three classes.
- Sampling frequency: 4385 Hz.



ESR:

- EEG Data.
- 11 500 samples.
- Two classes.
- Sampling frequency: 174 Hz.

Metrics:

- Mathews Correlation Coefficient (MCC).
- CR_G.

Models:

- 2D CNN.
- 1D CNN-transformer.

Loss function:

- Cross entropy (CE)

Experiment: influence of normalization

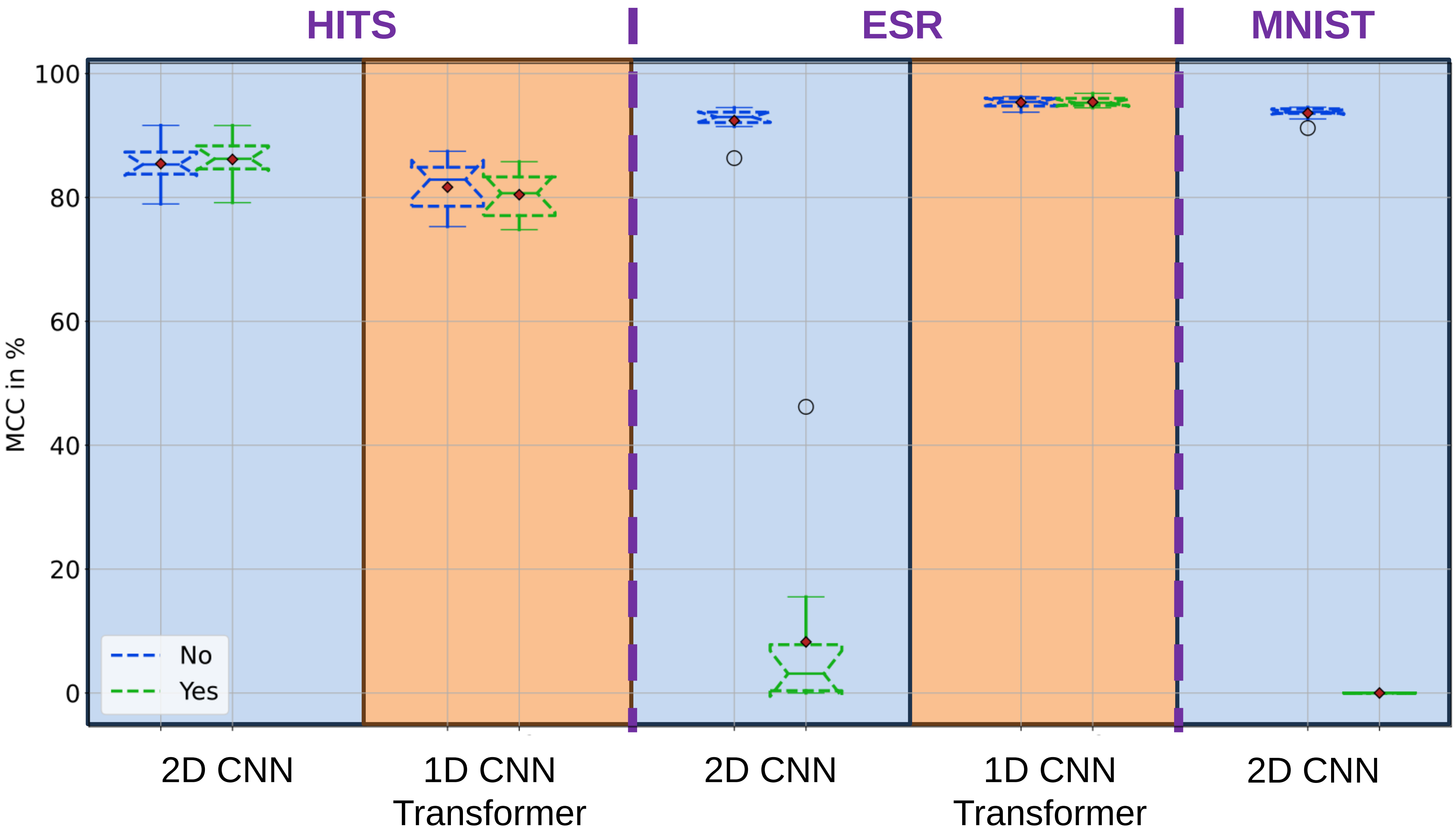


Figure – Influence of normalization on aTTQ from the **classification** perspective

Experiment: influence of normalization

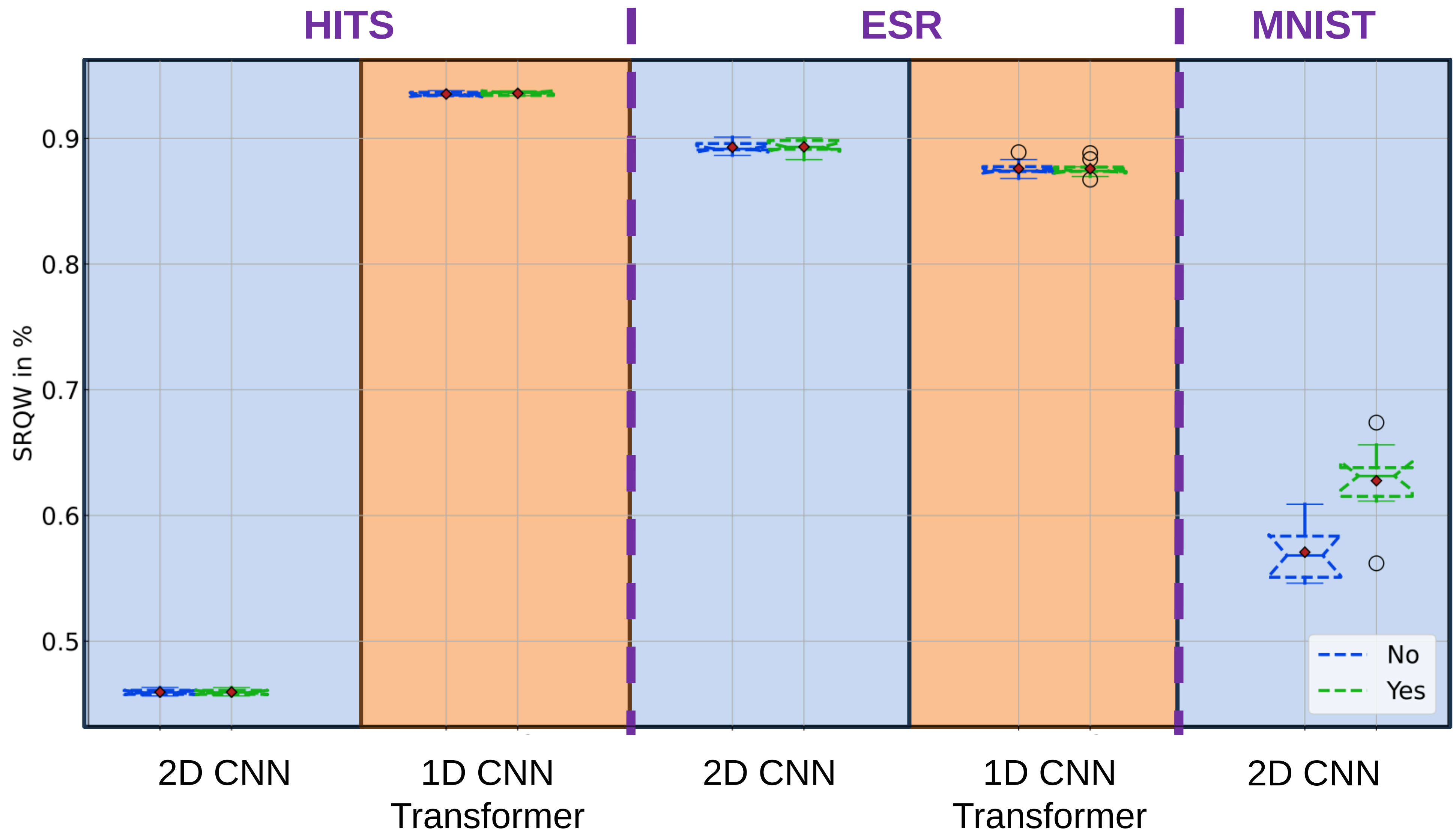
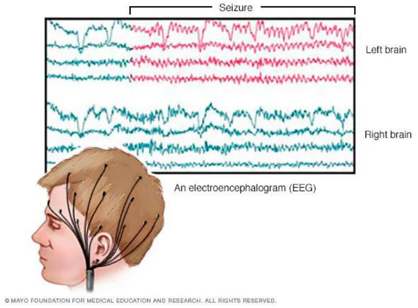


Figure – Influence of normalization on aTTQ from the **sparsity/compression** perspective

Experiment: influence of t_{min} and t_{max}

Objective:
- Study the influence of our trade-off parametrization t_{min} and t_{max}.

Dataset:



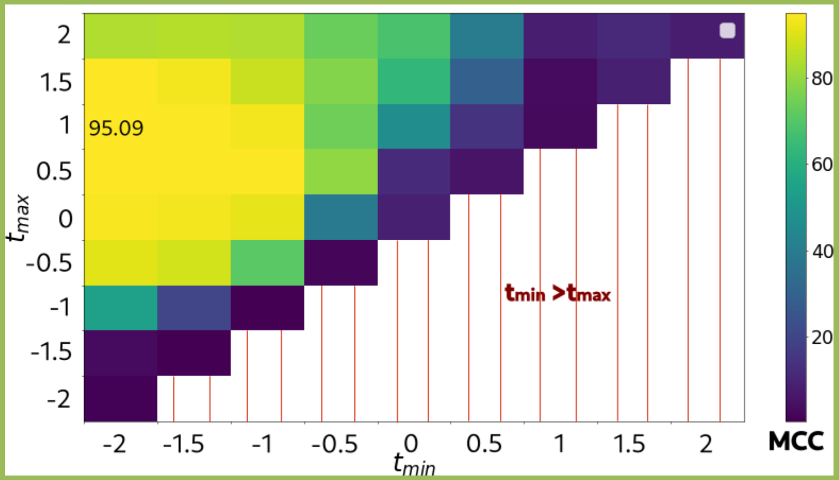
ESR:
- EEG Data.
- 11 500 samples.
- Two classes.
- Sampling frequency: 174 Hz.

Metrics:
- Matthews correlation coefficient (MCC).
- Sparsity rate of the quantized weights (SRQW).

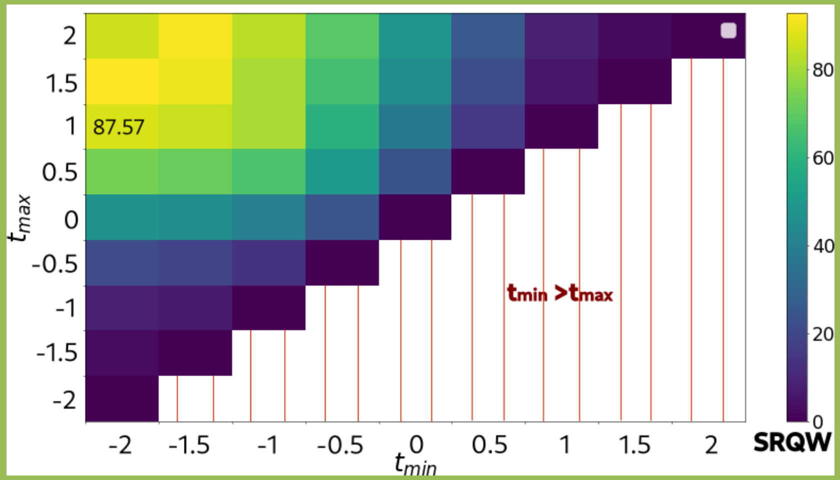
Model:
- 1D CNN-transformer.

Loss function:
- Cross entropy (CE)

ESR 1D CNN-transformer



MCC



SRQW

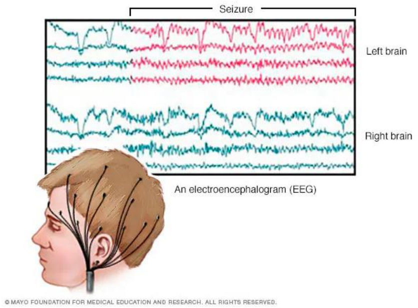
Figure – SMCC and SRQW for different values of t_{min} and t_{max}.

Experiment: influence of t_{min} and t_{max}

Objective:

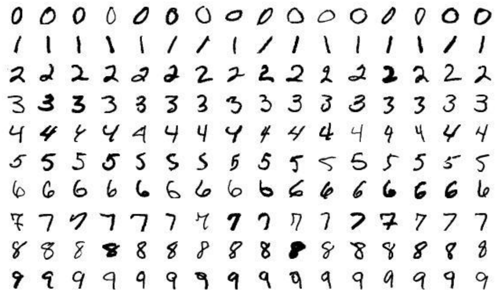
- Study the influence of our trade-off parametrization t_{min} and t_{max}.

Datasets:



ESR:

- EEG Data.
- 11 500 samples.
- Two classes.
- Sampling frequency: 174 Hz.



MNIST subset:

- 28x28 images.
- 20 000 samples.
- Ten classes.

Metrics:

- Mathews Correlation Coefficient (MCC).
- CR_G.

Models:

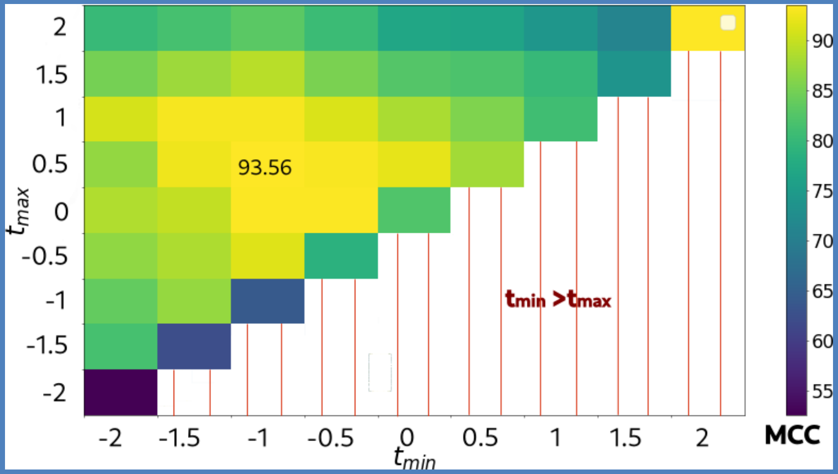
- 2D CNN.
- 1D CNN-transformer.

Loss function:

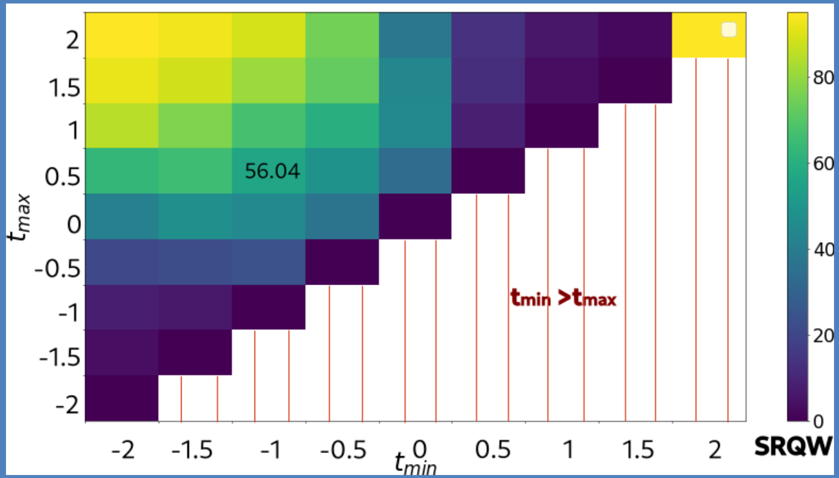
- Cross entropy (CE)

Experiment: influence of t_{min} and t_{max}

MNIST
2D CNN

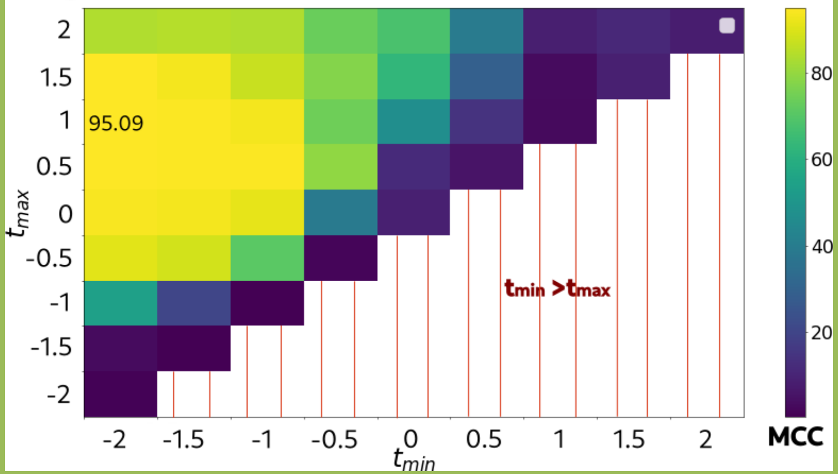


MCC

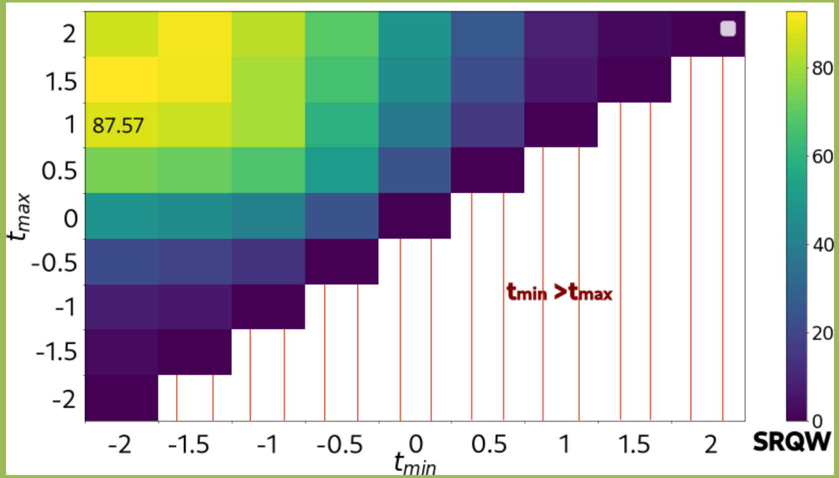


SRQW

ESR
1D CNN-transformer



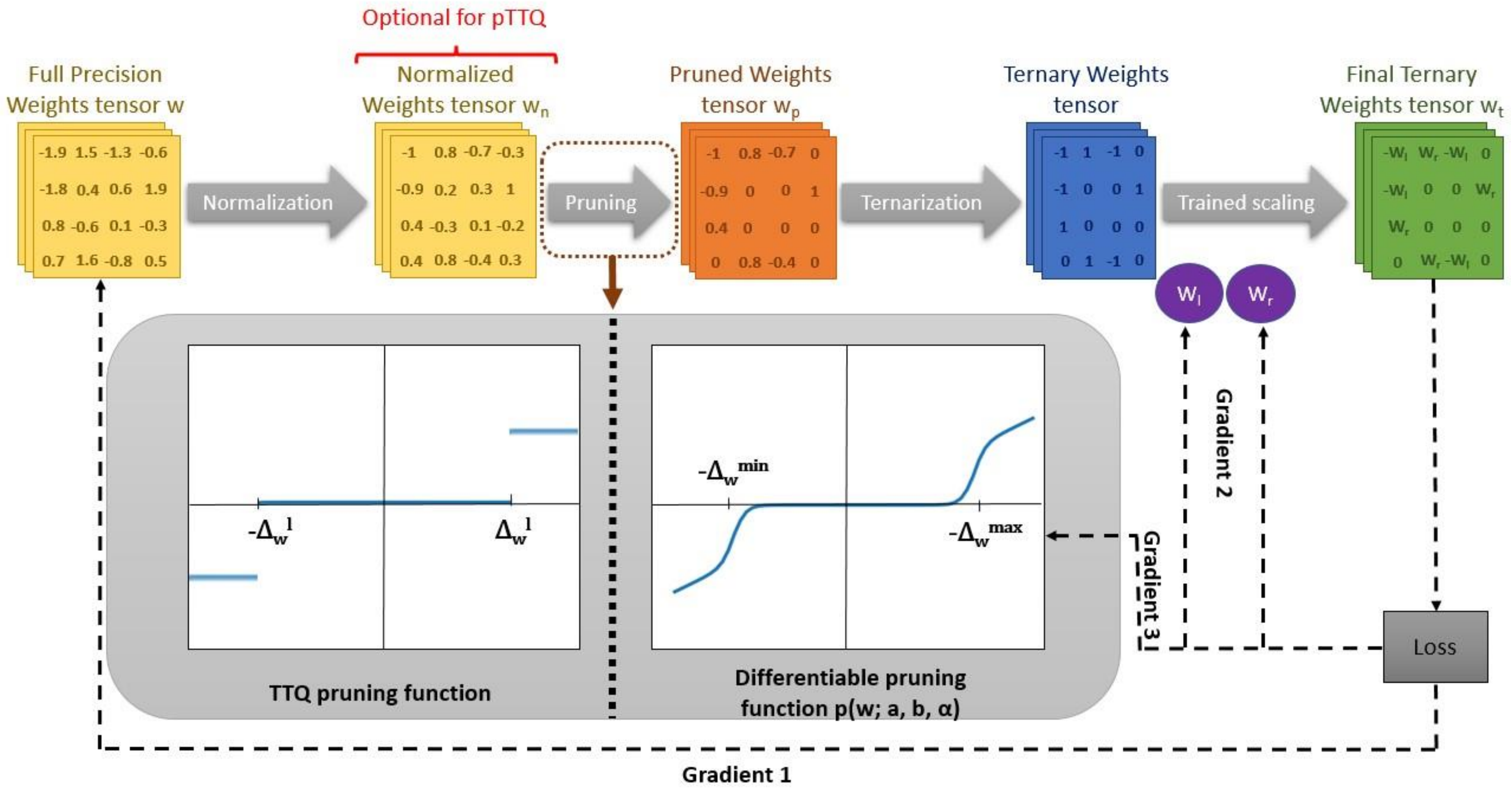
MCC



SRQW

Figure – SMCC and SRQW for different values of t_{min} and t_{max}.

Pruned trained ternary quantization (pTTQ)



Pruned trained ternary quantization (pTTQ)

Pruning function:

Slope of thresholding

$$p(w; t_{min}, t_{max}, \alpha) = ReLU(w - \Delta_w(t_{max})) + \Delta_w(t_{max}) * S(\alpha \times (w - \Delta_w(t_{max})))$$

$$- ReLU(-w - \Delta_w(t_{min})) - \Delta_w(t_{min}) * S(\alpha \times (-w - \Delta_w(t_{min})))$$

Sigmoid function

$$\Delta_w : t \to \mu_w + t \times \sigma_w$$

Mean

Standard deviation

Pruned trained ternary quantization (pTTQ)

Gradients:

Heaviside function

$$\frac{\partial p}{\partial t_{min}}(w; t_{min}, t_{max}, \alpha) = \sigma_w \times H(-w - \Delta_w^{min}) - \sigma_w \times S(\alpha \times (-w - \Delta_w^{min}))$$
$$+ \sigma_w \times \alpha \times \Delta_w^{min} \times S(\alpha \times (-w - \Delta_w^{min})) \times (1 - S(-w - \Delta_w^{min}))$$

$$\frac{\partial p}{\partial t_{min}}(w; t_{min}, t_{max}, \alpha) = -\sigma_w \times H(w - \Delta_w^{max}) + \sigma_w \times S(\alpha \times (w - \Delta_w^{max}))$$
$$- \sigma_w \times \alpha \times \Delta_w^{max} \times S(\alpha \times (w - \Delta_w^{max})) \times (1 - S(w - \Delta_w^{max}))$$

Pruned trained ternary quantization (pTTQ)

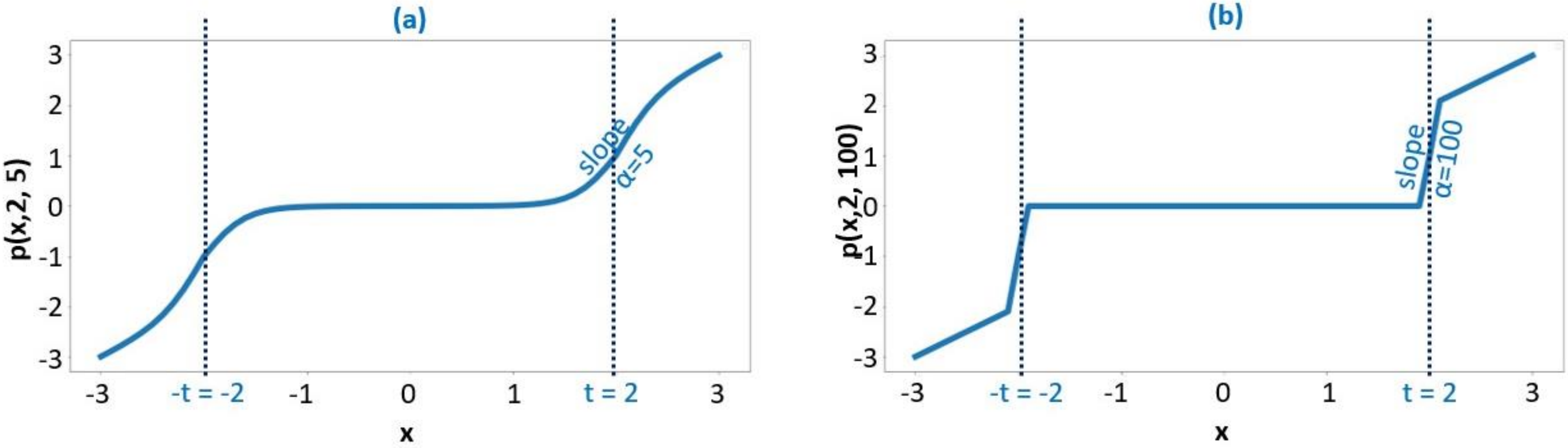


Figure – Examples of pruning functions for different thresholds and values of α

Pruned trained ternary quantization (pTTQ)

Dataset	Model	Quant. method	$CR_G^T \uparrow$	$CR_G^Q \uparrow$	$SRQW$	$EC_G^T \uparrow$	MCC ↑	Δ MCC ↑
HITS	2D CNN	FP	-	-	-	-	89.84 ± 3.09	-
		DoReFa (33)	$\mathbf{89.18 \pm 0}$	$\mathbf{96.87 \pm 0}$	-	3.54 ± 0	85.05 ± 5.96	-4.79
		TTQ (13)	24.96 ± 2.25	27.12 ± 2.44	28.96 ± 2.12	$\mathit{23.42 \pm 1.30}$	$\mathit{86.82 \pm 2.29}$	$\mathit{-3.02}$
		pTTQ	$\mathit{75.54 \pm 3.39}$	$\mathit{82.06 \pm 3.69}$	$\mathbf{83.12 \pm 3.47}$	$\mathbf{75.53 \pm 1.53}$	$\mathbf{89.33 \pm 4.45}$	$\mathbf{-0.55}$
	1D CNN-trans.	FP	-	-	-	-	82.64 ± 1.77	-
		DoReFa (33)	$\mathbf{14.50 \pm 0}$	$\mathbf{96.87 \pm 0}$	-	0.37 ± 0.03	$\mathit{84.07 \pm 3.11}$	$\mathit{+1.43}$
		TTQ (13)	0.14 ± 0.04	0.91 ± 0.27	6.75 ± 0.26	$\mathit{1.88 \pm 0.03}$	83.22 ± 2.36	$+0.58$
		pTTQ	$\mathit{8.37 \pm 0.05}$	$\mathit{55.89 \pm 0.34}$	$\mathbf{58.50 \pm 0.32}$	$\mathbf{2.01 \pm 0.05}$	$\mathbf{85.12 \pm 1.94}$	$\mathbf{+2.48}$
ESR	2D CNN	FP	-	-	-	-	92.81 ± 3.53	-
		DoReFa (33)	$\mathbf{96.40 \pm 0}$	$\mathbf{96.87 \pm 0}$	-	29.90 ± 0	$\mathit{94.12 \pm 0.87}$	$\mathit{+1.31}$
		TTQ (13)	85.61 ± 1.37	86.03 ± 1.37	86.59 ± 1.29	$\mathit{76.45 \pm 1.13}$	$\mathbf{95.00 \pm 1.11}$	$\mathit{+2.19}$
		pTTQ	$\mathit{93.35 \pm 0.96}$	$\mathit{93.80 \pm 0.96}$	$\mathbf{94.17 \pm 0.91}$	$\mathbf{90.32 \pm 0.69}$	92.23 ± 2.32	-0.58
	1D CNN-trans.	FP	-	-	-	-	94.33 ± 1.51	-
		DoReFa (33)	$\mathit{23.46 \pm 0}$	$\mathit{96.86 \pm 0}$	-	0.90 ± 0	$\mathbf{96.79 \pm 0.55}$	$\mathbf{+2.46}$
		TTQ (13)	11.40 ± 2.61	47.07 ± 10.79	50.22 ± 10.16	$\mathit{3.21 \pm 0.66}$	96.25 ± 0.79	$+1.92$
		pTTQ	$\mathbf{23.86 \pm 0.04}$	$\mathbf{98.54 \pm 0.16}$	$\mathbf{98.67 \pm 0.15}$	$\mathbf{6.04 \pm 0.01}$	$\mathit{96.35 \pm 0.95}$	$\mathit{+2.02}$
MNIST	2D MNIST CNN	-	-	-	-	-	94.39 ± 0.46	-
		DoReFa (33)	$\mathbf{51.67 \pm 0}$	$\mathbf{96.84 \pm 0}$	-	$\mathit{3.28 \pm 0}$	87.03 ± 7.14	-7.36
		TTQ (13)	13.86 ± 2.33	25.97 ± 4.37	30.40 ± 4.12	2.58 ± 0.35	$\mathbf{92.09 \pm 0.89}$	$\mathbf{-2.30}$
		pTTQ	$\mathit{33.92 \pm 1.02}$	$\mathit{63.58 \pm 1.92}$	$\mathbf{65.79 \pm 1.80}$	$\mathbf{6.10 \pm 0.15}$	$\mathit{91.01 \pm 0.61}$	$\mathit{-3.38}$

Table – Comparison of pTTQ with other state-of-the-art methods

Experiment: pTTQ SOTA comparison

Dataset	Model	Quant. method	$CR_G^T \uparrow$	$CR_G^Q \uparrow$	$SRQW$	$EC_G^T \uparrow$	MCC ↑	Δ MCC ↑
HITS	2D CNN	FP	-	-	-	-	89.84 ± 3.09	-
		DoReFa [33]	**89.18 ± 0**	**96.87 ± 0**	-	3.67 ± 0	85.05 ± 5.96	−4.79
		TTQ [13]	24.96 ± 2.25	27.12 ± 2.44	28.96 ± 2.12	*23.13 ± 1.27*	*86.82 ± 2.29*	*−3.02*
		pTTQ	*75.54 ± 3.39*	*82.06 ± 3.69*	**83.12 ± 3.47**	**75.26 ± 1.61**	**89.33 ± 4.45**	**−0.55**
	1D CNN-trans.	FP	-	-	-	-	82.64 ± 1.77	-
		DoReFa [33]	**14.50 ± 0**	**96.87 ± 0**	-	0.32 ± 0.03	*84.07 ± 3.11*	*+1.43*
		TTQ [13]	0.14 ± 0.04	0.91 ± 0.27	6.75 ± 0.26	**1.86 ± 0.03**	83.22 ± 2.36	+0.58
		pTTQ	*8.37 ± 0.05*	*55.89 ± 0.34*	**58.50 ± 0.32**	*1.82 ± 0.04*	**85.12 ± 1.94**	**+2.48**
ESR	2D CNN	FP	-	-	-	-	92.81 ± 3.53	-
		DoReFa [33]	**96.40 ± 0**	**96.87 ± 0**	-	42.65 ± 0	*94.12 ± 0.87*	*+1.31*
		TTQ [13]	85.61 ± 1.37	86.03 ± 1.37	86.59 ± 1.29	*72.01 ± 1.08*	**95.00 ± 1.11**	*+2.19*
		pTTQ	*93.35 ± 0.96*	*93.80 ± 0.96*	**94.17 ± 0.91**	**88.68 ± 0.60**	92.23 ± 2.32	−0.58
	1D CNN-trans.	FP	-	-	-	-	94.33 ± 1.51	-
		DoReFa [33]	*23.46 ± 0*	*96.86 ± 0*	-	0.91 ± 3.69	**96.79 ± 0.55**	**+2.46**
		TTQ [13]	11.40 ± 2.61	47.07 ± 10.79	50.22 ± 10.16	*2.79 ± 0.57*	96.25 ± 0.79	+1.92
		pTTQ	**23.86 ± 0.04**	**98.54 ± 0.16**	**98.67 ± 0.15**	**5.21 ± 0.01**	*96.35 ± 0.95*	*+2.02*
MNIST	2D MNIST CNN	-	-	-	-	-	94.39 ± 0.46	-
		DoReFa [33]	**51.67 ± 0**	**96.84 ± 0**	-	*3.39 ± 6.94*	87.03 ± 7.14	−7.36
		TTQ [13]	13.86 ± 2.33	25.97 ± 4.37	30.40 ± 4.12	1.65 ± 0.16	**92.09 ± 0.89**	**−2.30**
		pTTQ	*33.92 ± 1.02*	*63.58 ± 1.92*	**65.79 ± 1.80**	**4.10 ± 0.10**	*91.01 ± 0.61*	*−3.38*

Table – Comparison of **pTTQ** with other quantization methods

Conclusion et perspectives

Conclusion

Dataset creation and annotation

- Semi-supervised data annotation
- Soft labelling (annotation)

Novel methodology for **semi-automatic data annotation** based on local-quality metrics.

Selection strategy of the best **projection** obtained by a dimensionality reduction technique.

Use robust loss functions to improve the classification performances of a **classifier trained** on a **noisy** semi-automatic labeled **dataset.**

Conclusion

Multiple representations →

- Different models with different inputs
- Multi-feature models

Novel **hybrid CNN-transformer** models, **exploiting** the **complementarity** between the **temporal** and **spectral characteristics** of a medical signal.

Guided and **regularized intermediate fusion** approach, improving generalization while handling **imbalanced** datasets and **label-noise**.

Late-fusion mechanisms, based on **learnable** and **interpretable attention weights**.

Conclusion

Resource hungry models →

- Lite models
- Model compression
- (Soft labelling training)

→ **Novel ternarization heuristic**, based on the weights' statistics.

→ **Direct asymmetric pruning** before ternarization, allowing a **better trade-off** between compression, energy, and classification.

→ **Asymmetric parametrization** of the sparsity rate, **controlling** the abovementioned **trade-off**.

Perspectives

Dataset creation and annotation →

- Semi-supervised data annotation
- Soft labelling (annotation)

→ **More complex encoding models** (VAE, GANs, diffusion models, ...)

→ **Stronger regularization** (DEC, contrastive learning, more complex projection metrics, ...)

→ **Active learning** by proposing to human experts the most difficult samples

Perspectives

Multiple representations

- Different models with different inputs
- Multi-feature models

Test other types of models (LSTM, ViT, ResNet, …) **and datasets** (medical and non-medical)

Use **other representations** of the raw signal (cochleagram, binary encodings, chromagram, …)

Use **other** types of **regularization** (contrastive learning with weak supervision, link constraints, …)

Perspectives

Resource hungry models →

- Lite models
- Model compression
- (Soft labelling training)

Differentiable pruning function, with asymmetric learnable parameters

Mixed quantization to completely quantize the models with different precisions

Hardware implementation to take advantage of the compressed models

Perspectives

Soft labelling →

- Capture expert uncertainty
- Noise robustness

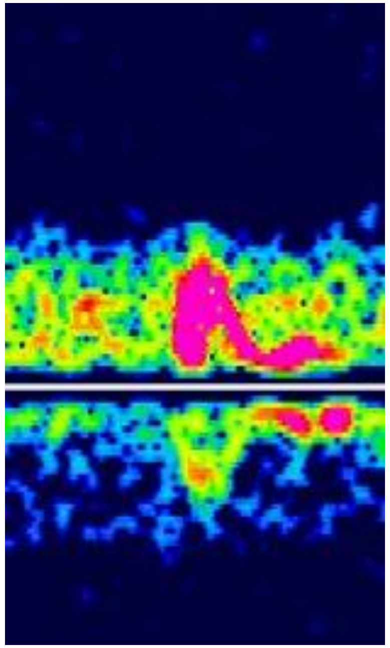
→ **Take advantage of soft annotations** using **soft-lables loss functions** (soft CE, Jensen-Shannon divergence, …), to capture the human expert uncertainty,

→ New **loss functions robust** against **soft-label noise** (geometric mean Jensen-Shannon divergence).

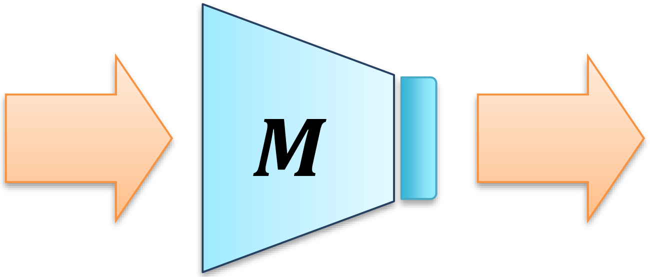
→ **Semi-automatic soft label annotation evaluation.**

Soft labels

Working with soft labels (vs hard labels)



Sample X



Deep model

Soft prediction

$$M(X)_S = \begin{pmatrix} y_S^{Art} \\ y_S^{GE} \\ y_S^{SE} \end{pmatrix} = \begin{pmatrix} 0.1 \\ 0.3 \\ \boxed{0.6} \end{pmatrix}$$

conversion to
hard prediction
→ highest score

$$M(X)_H = \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}$$

Soft labels

Loss functions

Loss	soft labels	noise tolerant
$L_{CE}(y_H, M(X)_H) = H(y_H, M(X)_H)$ cross-entropy (baseline)	✖	✖
$L_{SoftCE}(y_S, M(X)_S) = H(y_S, M(X)_S)$	✓	✖
$L_{SymCE}(y_H, M(X)_H) = \alpha \times H(y_H, M(X)_H) + \beta \times H(M(X)_H, y_H)$	✖	✓
$L_{JSD}(y_S, M(X)_S) = \frac{1}{2} \times (KL(y_S, m_S) + KL(M(X)_S, m_S))$ with $m_S = \frac{1}{2} \times (y_S + M(X)_S)$	✓	✖

Soft labels

Adding symmetric noise to soft labels

noise rate ζ (in %)

$$y_S \begin{pmatrix} 0.1 \\ 0.3 \\ \boxed{0.6} \end{pmatrix} \begin{matrix} \text{Art} \\ \text{GE} \\ \text{SE} \end{matrix}$$

Highest score moves to another class with probability ζ

with probability $\frac{\zeta}{C - 1}$ → $\overline{y_S} = \begin{pmatrix} \boxed{0.6} \\ 0.3 \\ 0.1 \end{pmatrix}$ **Noisy**

with probability $\frac{\zeta}{C - 1}$ → $\overline{y_S} = \begin{pmatrix} 0.1 \\ \boxed{0.6} \\ 0.3 \end{pmatrix}$ **Noisy**

with probability $1 - \zeta$ → $\overline{y_S} = \begin{pmatrix} 0.1 \\ 0.3 \\ \boxed{0.6} \end{pmatrix}$ **Unmodified**

Soft labels

Adding symmetric noise to soft labels

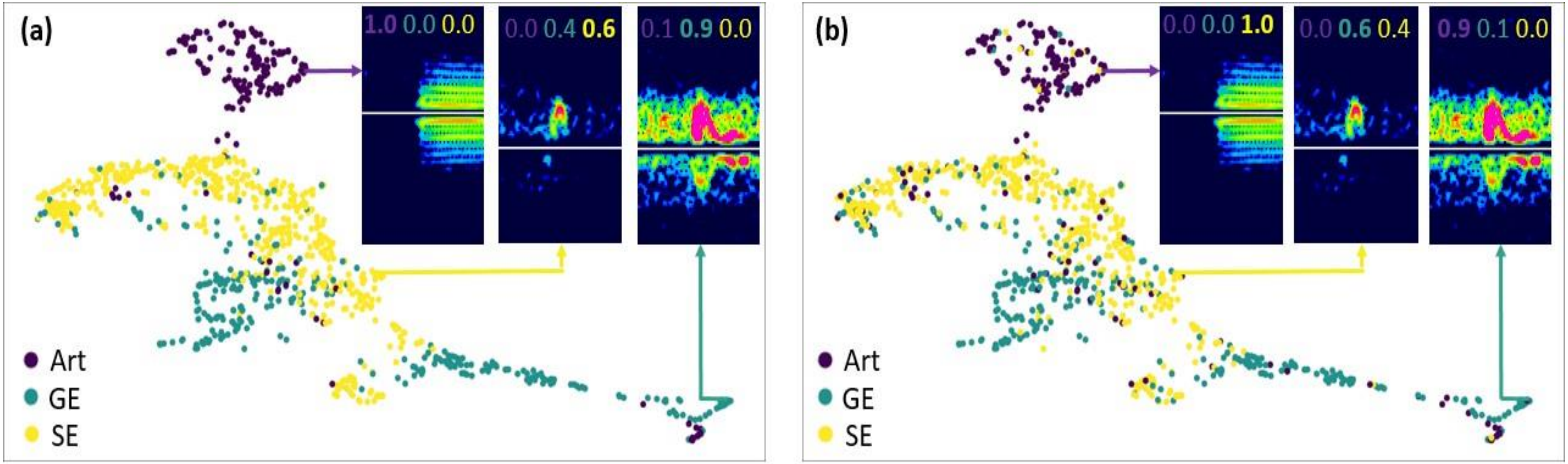
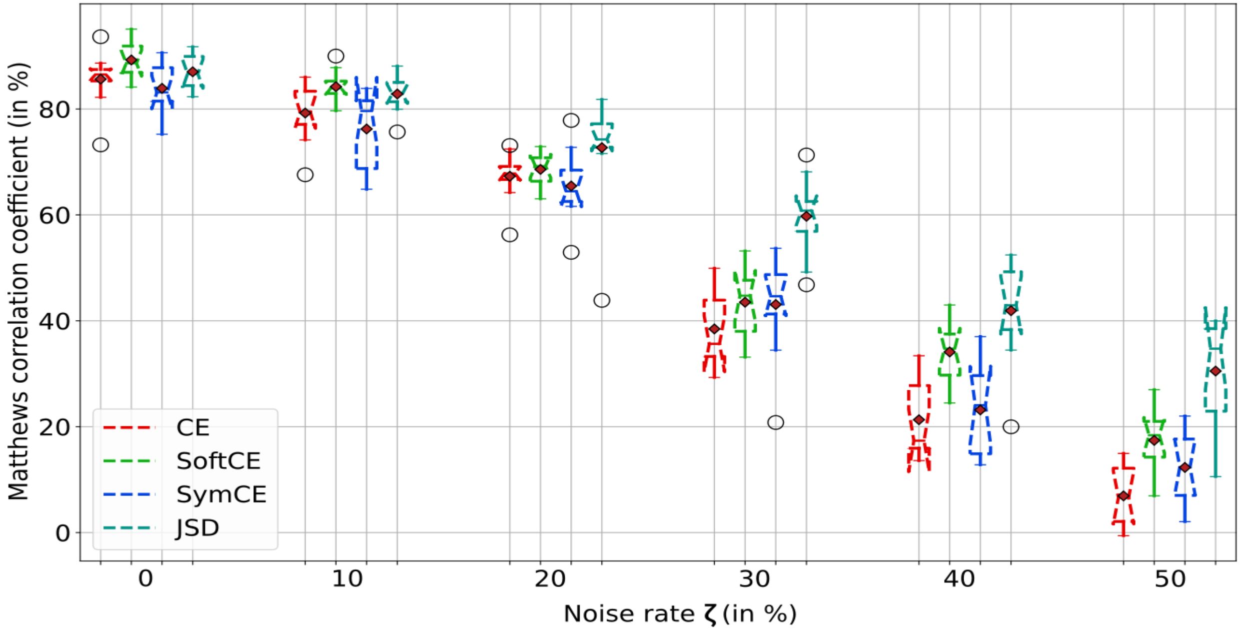


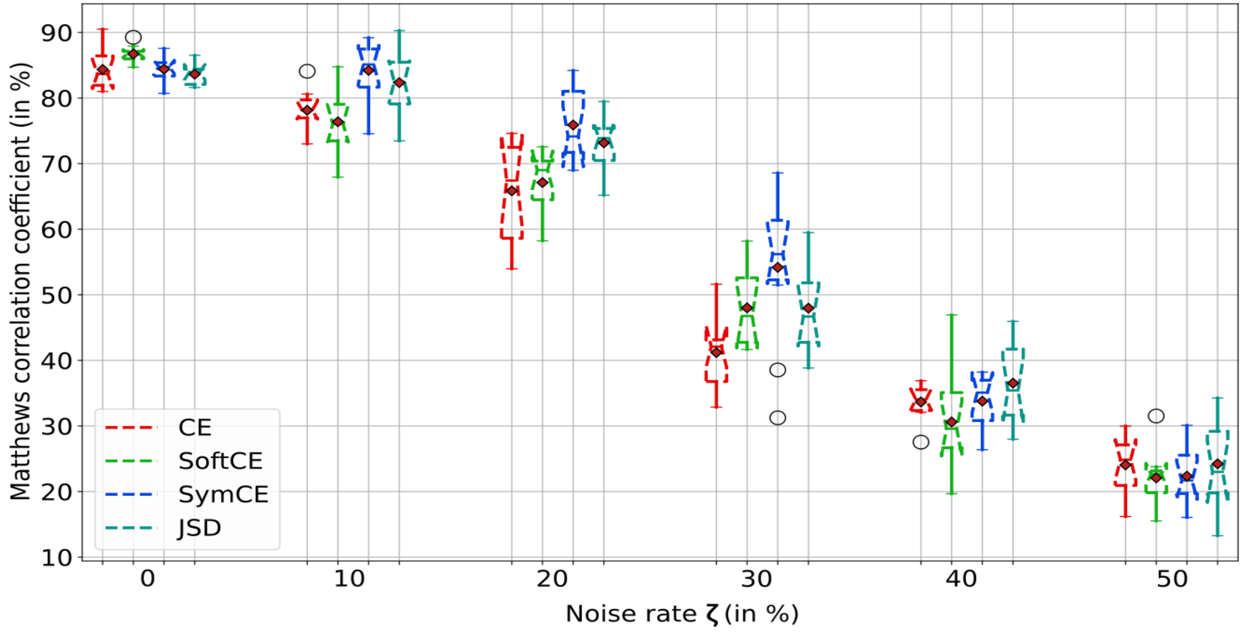
Figure - (a) HITS dataset without noise, **(b)** HITS dataset with 10% of symmetric noise in the soft labels.

Soft labels

Soft labels noise resistance



(a) 2D time-frequency CNN

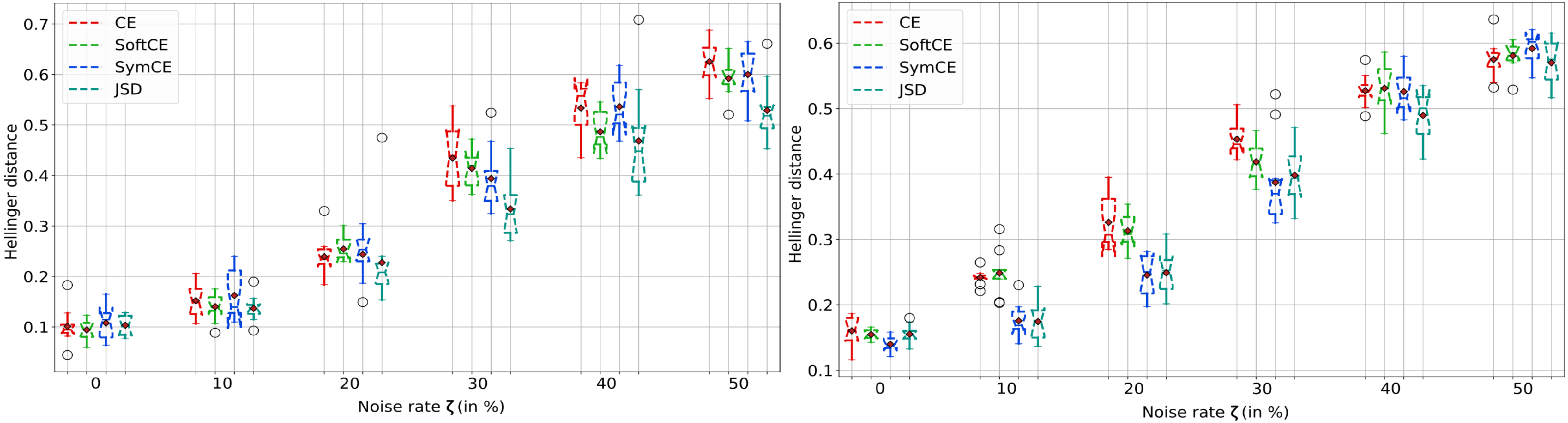


(b) Doppler signal 1D CNN-transformer

Figure - Classification performance of two types of models trained using the presented soft and hard label loss function

Soft labels

Uncertainty capturing



(a) 2D time-frequency CNN

(b) Doppler signal 1D CNN-transformer

Figure - Uncertainty capturing evaluation of two types of models trained using the presented soft and hard label loss function

Soft labels

Geometric Mean Jensen-Shannon Divergence (GEO JSD)

$$JSDR(P||Q) = \propto (1 - \propto)[\boldsymbol{\beta}(H(P,P) - H(Q,P)) + \underbrace{\boldsymbol{\Upsilon}(H(Q,Q) - H(P,Q))]}_{\text{Robustesse au bruit prouvée théoriquement}}$$

Soft labels

Résultats préliminaires GEO JSD

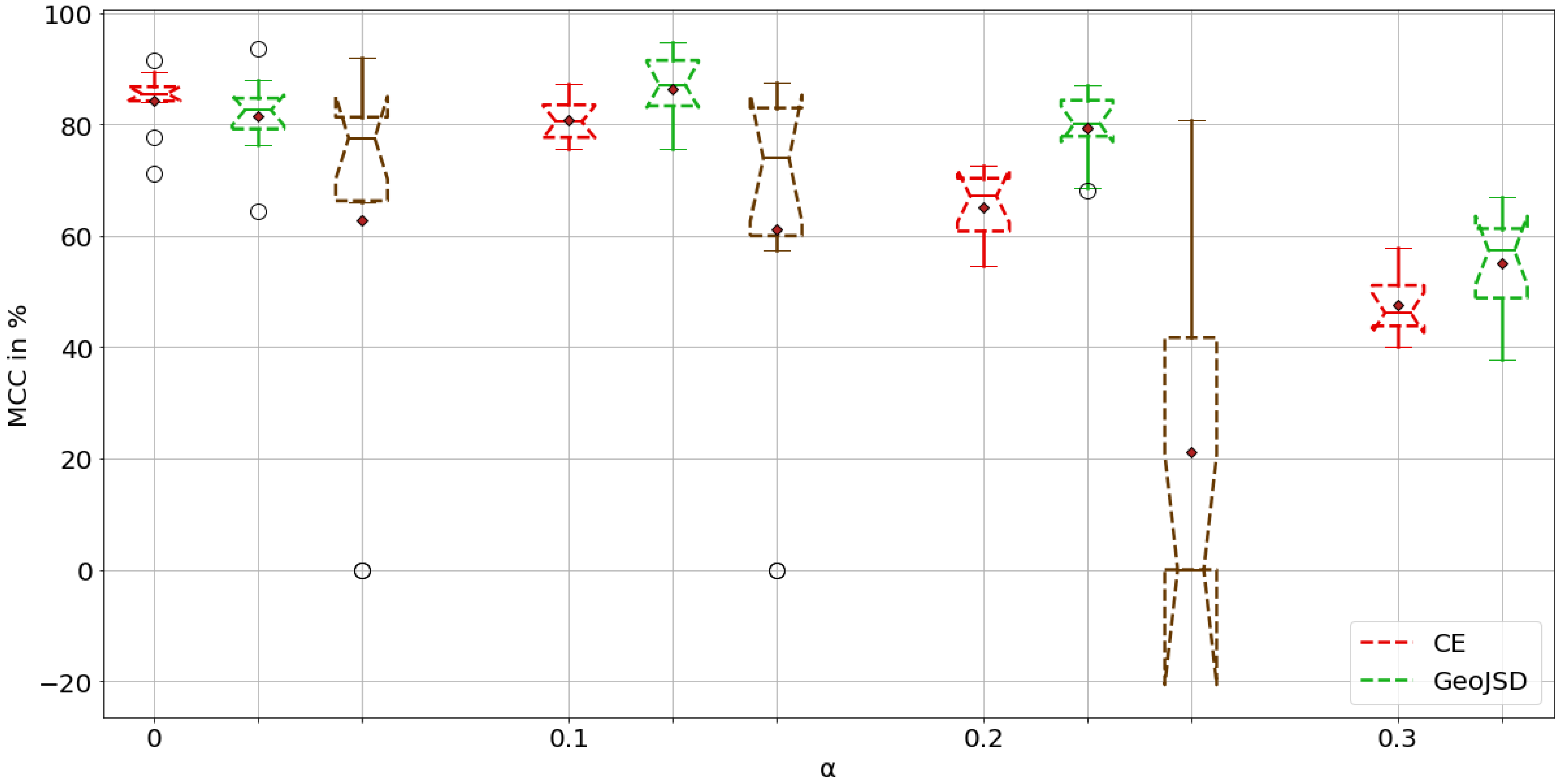


Figure – Résultats HITS-small

Soft labels

Résultats préliminaires GEO JSD

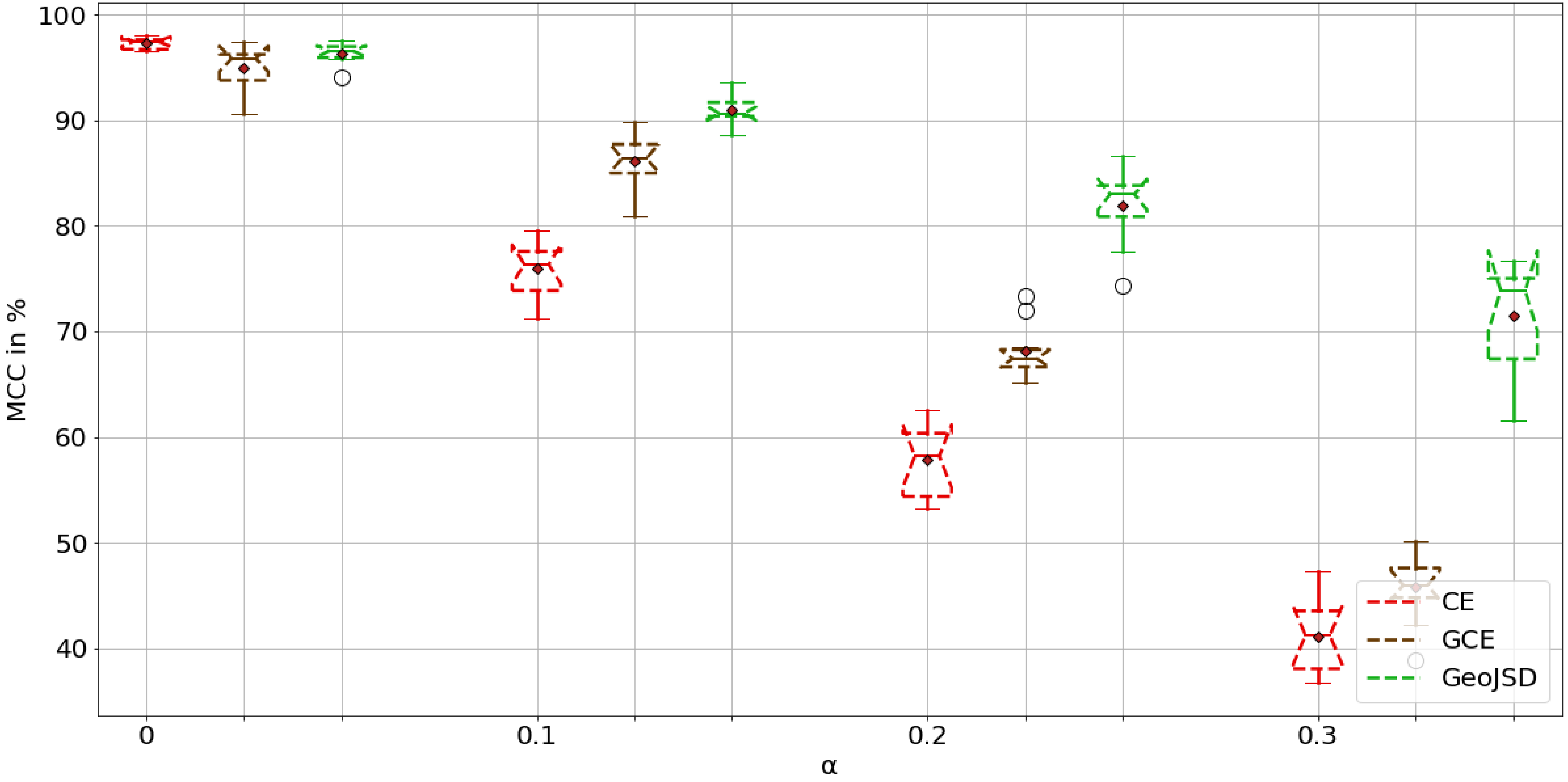


Figure – Résultats PTB

Mathews Correlation Coefficient (Binary classification)

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

$$\Rightarrow \quad MCC = 0 \Leftrightarrow TP \times TN = FP \times FN$$

Random classifier !

Statistical tests for comparison

- Important hypothesis for several statistical tests ➔ **Independence of observations**.
  - For k-fold cross-validation:
    - One sample belongs to the training dataset is k-1 times

The mean estimates are not independent !

  - For repeated holdout:
    - The training and testing datasets are fixed during repetitions.

- **Solutions**
  - Create different datasets, one per repetition ➔ Not yet possible for the HITS.
    - Reduces training and testing samples per dataset.
  - 5x2 cross-validation ➔ Difficult to do it subject-wise.
  - Other tests without independence hypothesis ?

Choice of q hyperparameter for GCE

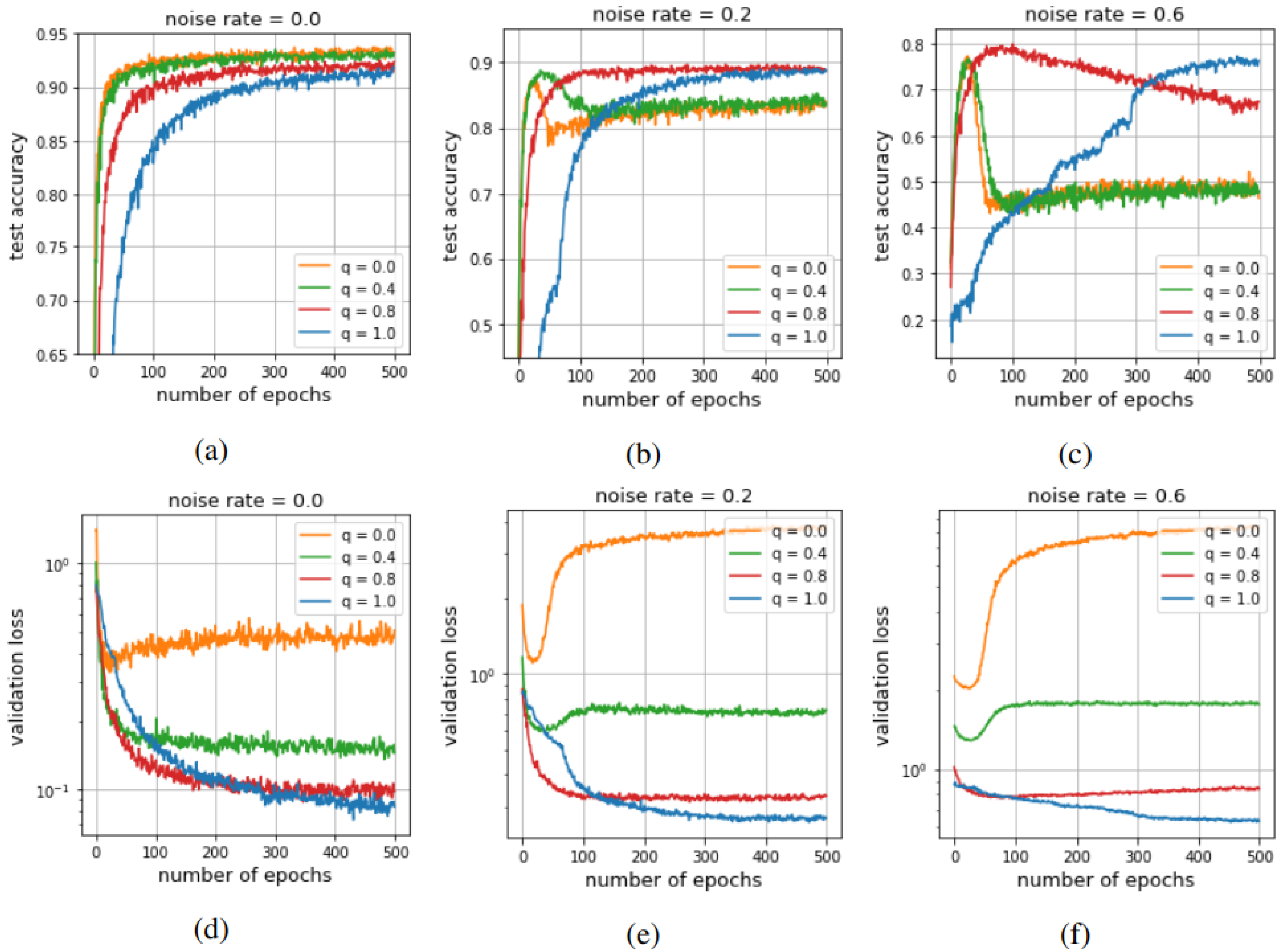


Figure – Test accuracy and validation GCE, for different values of q, on the XXX dataset (Zhang et Sabuncu 2018)

Automatic annotation vs Manual annotation

Split	No. patients	Total	SE	GE	Art.
Train	39	1541	456	610	6 198
Test	12	139	39	47	53

Table – HITS-small-I dataset.

Model	MCC
2D CNN	87.09 ± 4.31
1D CNN-trans.	79.17 ± 6.64
MIF-GR	**91.89 ± 2.64**

Table – Multi-feature GDCE compared to single feature models on a noisy semi-automatically labeled dataset **HITS-small-I**.

Split	No. patients	Total	SE	GE	Art.
Train	40	7 264	456	610	6 198
Test	11	1 421	240	392	789

Table – HITS-sada dataset.

Model	MCC
2D CNN	84.03 ± 1.20
1D CNN-trans.	85.74 ± 1.16
MIF-GR	**87.35 ± 0.85**

Table – Multi-feature GDCE compared to single feature models on a noisy semi-automatically labeled dataset **HITS-sada**.

- **Not the same test sets** between experiments, so results are not directly comparable.
- Test set of HITS-sada is harder.

Choice of the pruning parameters aTTQ

- **Choice of t_{min} and t_{max} is critical.**
  - **Bad choice:**
    - Poor classification performances.
    - Poor compression/energy performances
    - ➔ It **happens also for other methods** such as TTQ or TWN !
  - **Carefeul choice:**
    - **Great compression/energy/classification trade-off**.
- **Solutions**
  - Pruned trained ternary quantization with learnable threshold parameters !
  - Bayesian hyperparameter searching.
  - Larger study to understand influence of t_{min} and t_{max}.

Industrial application and impact on patient care

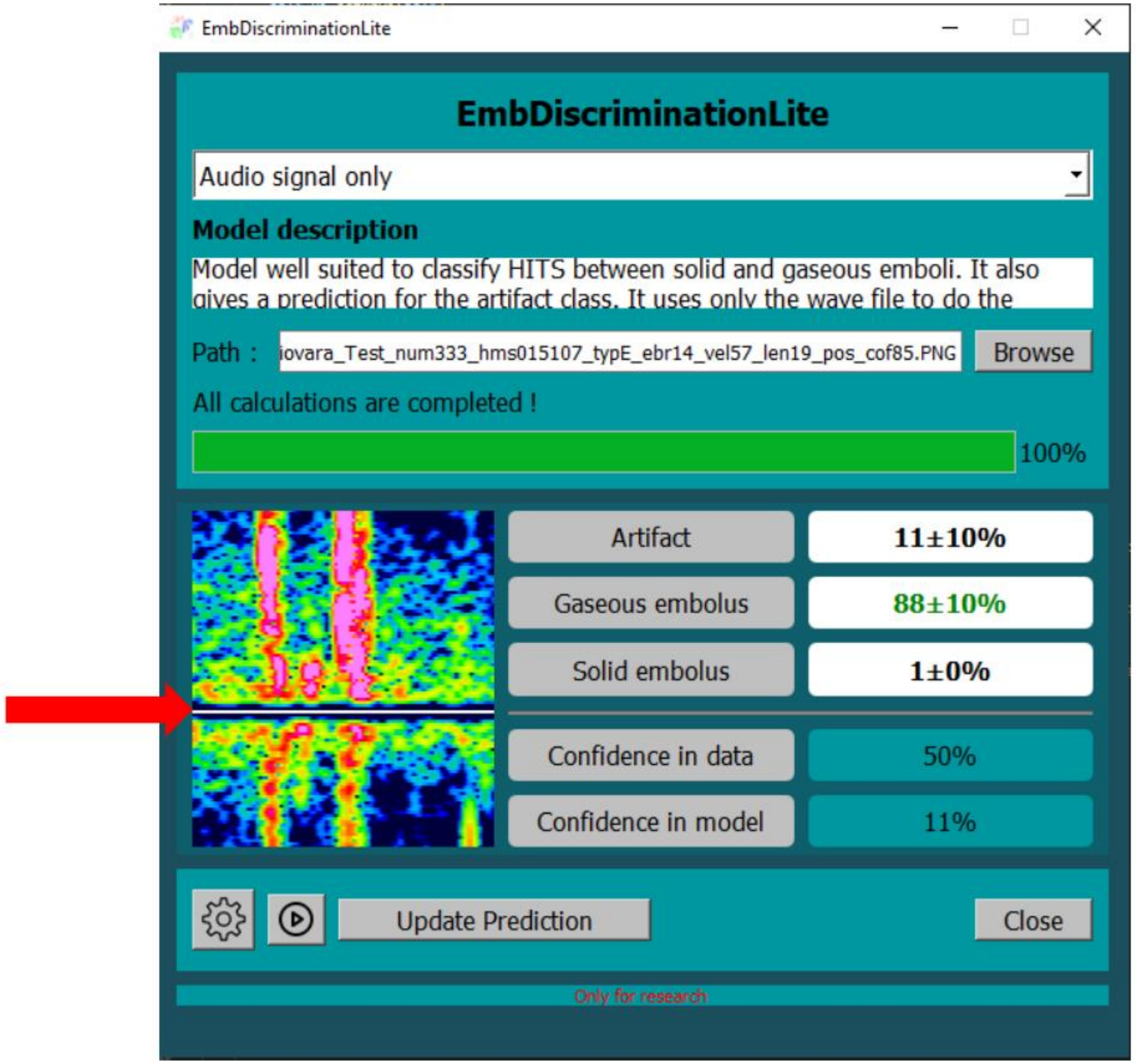
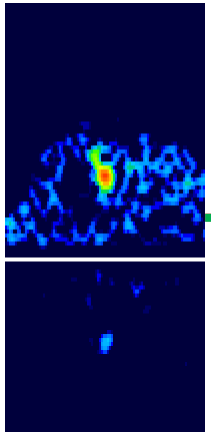


Figure – EmbDiscriminationLite application, deep learning classification module for ADMS for Atys Medical

Industrial application and impact on patient care

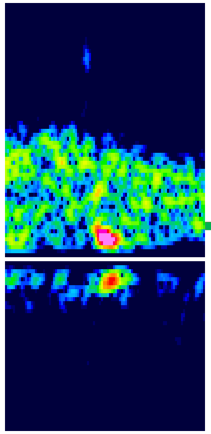
Solid embolus



Good diagnosis
Adapted treatment → Stroke prevention

Bad diagnosis
No treatment needed → Stroke risk

Artifact



Good diagnosis
No treatment needed

Bad diagnosis
Wrong treatment → Risk of complications

Model compression comparison with other SOTA method

Dataset	Model	Quant. method	$CR_G^T \uparrow$	$CR_G^Q \uparrow$	$SRQW$	$EC_G^T \uparrow$	MCC ↑	Δ MCC ↑
HITS	2D CNN	FP	-	-	-	-	89.84 ± 3.09	-
		DoReFa	**89.18 ± 0**	**96.87 ± 0**	-	3.54 ± 0	85.05 ± 5.96	−4.79
		TTQ	24.96 ± 2.25	27.12 ± 2.44	28.96 ± 2.12	23.42 ± 1.30	*86.82 ± 2.29*	*−3.02*
		aTTQ	42.98 ± 0.23	46.69 ± 0.25	*45.95 ± 0.21*	*44.04 ± 0.19*	86.14 ± 3.37	−3.70
		pTTQ	*75.54 ± 3.39*	*82.06 ± 3.69*	**83.12 ± 3.47**	**75.53 ± 1.53**	**89.33 ± 4.45**	**−0.55**
	1D CNN-trans.	FP	-	-	-	-	82.64 ± 1.77	-
		DoReFa	**14.50 ± 0**	**96.87 ± 0**	-	0.37 ± 0.03	*84.07 ± 3.11*	*+1.43*
		TTQ	0.14 ± 0.04	0.91 ± 0.27	6.75 ± 0.26	1.88 ± 0.03	83.22 ± 2.36	+0.58
		aTTQ	*13.94 ± 0.02*	*93.17 ± 0.16*	**93.53 ± 0.15**	**7.64 ± 0.11**	81.66 ± 4.17	−0.98
		pTTQ	8.37 ± 0.05	55.89 ± 0.34	*58.50 ± 0.32*	*2.01 ± 0.05*	**85.12 ± 1.94**	**+2.48**
ESR	2D CNN	FP	-	-	-	-	92.81 ± 3.53	-
		DoReFa	**96.40 ± 0**	**96.87 ± 0**	-	29.90 ± 0	*94.12 ± 0.87*	*+1.31*
		TTQ	85.61 ± 1.37	86.03 ± 1.37	86.59 ± 1.29	76.45 ± 1.13	**95.00 ± 1.11**	**+2.19**
		aTTQ	88.48 ± 0.44	88.91 ± 0.45	*89.30 ± 0.42*	*84.49 ± 0.33*	92.41 ± 2.22	−0.40
		pTTQ	*93.35 ± 0.96*	*93.80 ± 0.96*	**94.17 ± 0.91**	**90.32 ± 0.69**	92.23 ± 2.32	−0.58
	1D CNN-trans.	FP	-	-	-	-	94.33 ± 1.51	-
		DoReFa	*23.46 ± 0*	*96.86 ± 0*	-	0.90 ± 0	**96.79 ± 0.55**	**+2.46**
		TTQ	11.40 ± 2.61	47.07 ± 10.79	50.22 ± 10.16	3.21 ± 0.66	96.25 ± 0.79	+1.92
		aTTQ	21.02 ± 0.15	86.78 ± 0.63	*87.59 ± 0.59*	*5.37 ± 0.04*	95.34 ± 0.79	+1.01
		pTTQ	**23.86 ± 0.04**	**98.54 ± 0.16**	**98.67 ± 0.15**	**6.04 ± 0.01**	*96.35 ± 0.95*	*+2.02*
MNIST	2D MNIST CNN	-	-	-	-	-	94.39 ± 0.46	-
		DoReFa	**51.67 ± 0**	**96.84 ± 0**	-	3.28 ± 0	87.03 ± 7.14	−7.36
		TTQ	13.86 ± 2.33	25.97 ± 4.37	30.40 ± 4.12	2.58 ± 0.35	**92.09 ± 0.89**	*−2.30*
		aTTQ	28.98 ± 1.26	54.32 ± 2.36	*57.08 ± 2.22*	*4.97 ± 0.22*	93.62 ± 0.96	**−0.77**
		pTTQ	*33.92 ± 1.02*	*63.58 ± 1.92*	**65.79 ± 1.80**	**6.10 ± 0.15**	*91.01 ± 0.61*	−3.38

Table – Comparison of aTTQ with other state-of-the-art methods

Difficulty of measuring energy consumption on real CPU/GPU

- **Energy consumption depends on**
  - Used hardware and the model.
  - Operations implementations.
  - Optimization of the trained models.

- **What is implemented ?**
  - Some sparse operations in PyTorch (Beta version).
  - Simulated quantization ➔ All operations are treated as 32 bits operations.

Solution ➔ **Simulation (difficult)**

- **Current codes do not allow efficient operations on common hardware**
  - Specialized hardware is needed for further improvements.