Enhancing Time Series Classification with Diversity-Driven Neural Network Ensembles

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1. Introduction and Literature Review
2. Proposed Method
3. Experimental Evaluation

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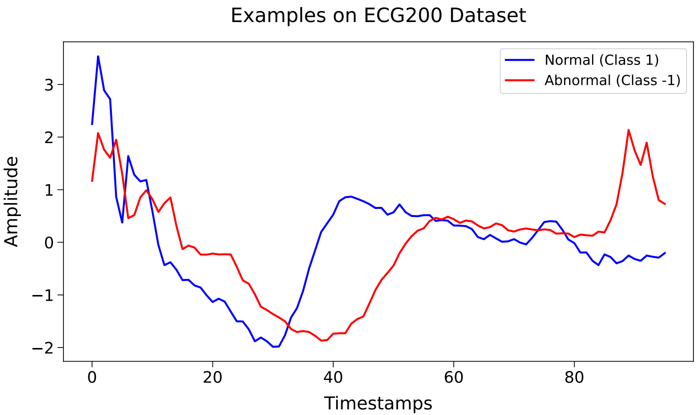
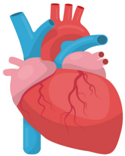
Time Series Data



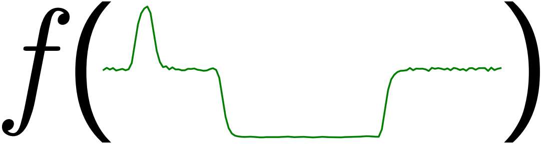


[1]

[1] Dau, Hoang Anh, et al. "The UCR time series archive." IEEE/CAA Journal of Automatica Sinica 6.6 (2019): 1293-1305.

Time Series Classification (TSC)

Time Series Classification Task



- f is a classifier
- f assigns a label y to an input sample
- $y \in \{0, \ldots, C-1\}$, with the C number of classes

Deep Learning approaches for TSC

- Deep Learning (DL) for TSC
  Best performing DL approaches for TSC based on Convolutional Neural Networks

Reference: Middlehurst, Matthew, Patrick Schäfer, and Anthony Bagnall. "Bake off redux: a review and experimental evaluation of recent time series classification algorithms." Data Mining and Knowledge Discovery 38.4 (2024): 1958-2031.

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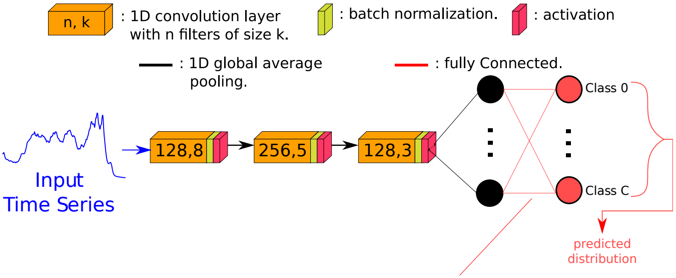

Fully Convolutional Network (FCN)

Reference: Ismail Fawaz, Hassan, et al. (2019). "Deep Learning for Time Series Classification: A Review." Data Mining and Knowledge Discovery, 33(4), 917–963.

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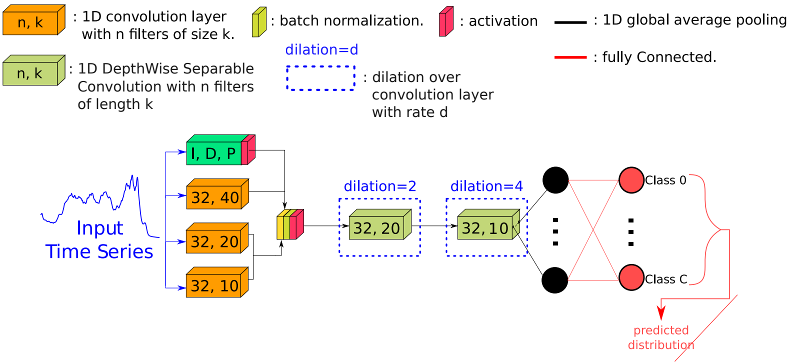

Lightweight InceptionTime Ensemble (LITE)

Reference: Ismail Fawaz, Hassan, et al. (2019). "Deep Learning for Time Series Classification: A Review." Data Mining and Knowledge Discovery, 33(4), 917–963.

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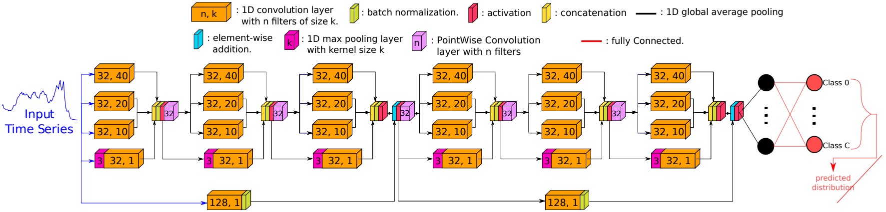

InceptionTime Architecture

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Motivation

- Current state-of-the-art deep learning-based TSC models are ensemble-based:
  - Inception**Time**
  - H-Inception**Time**
  - LITE**Time**

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  - Feature diversity
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- Why do ensembles often perform better:
  - Feature diversity
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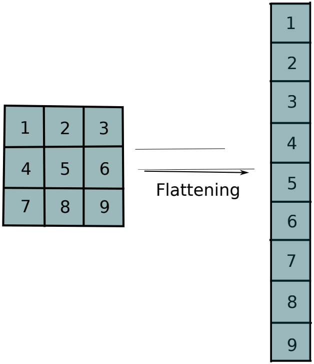
- **Can we improve the efficiency of ensemble models while enhancing diversity among their members?**

Orthogonality in Vision Models

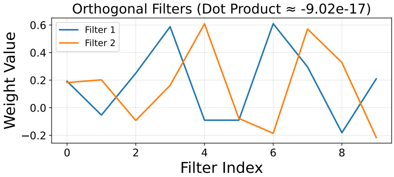
- Some vision models apply orthogonality constraints on filter weights (Yang et al.; Ayinde et al.; Wang et al.).



References:
Yang et al. *Orthogonality loss: Learning discriminative representations for face recognition* IEEE Trans. Circuits Syst. Video Technol., 31(6), 2301–2314, 2020.
Ayinde et al. *Regularizing deep neural networks by enhancing diversity in feature extraction* IEEE Trans. Neural Netw. Learn. Syst., 30(9), 2650–2661, 2019.
Wang et al. *Orthogonal convolutional neural networks.* CVF, 2020.

Rethinking Diversity

- By shifting filter position it is possible to achieve orthogonality



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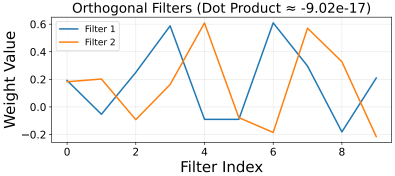

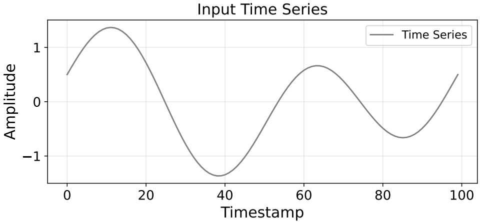

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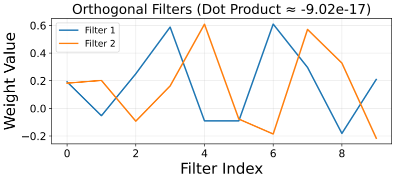

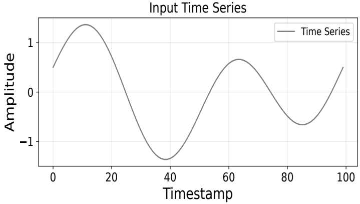

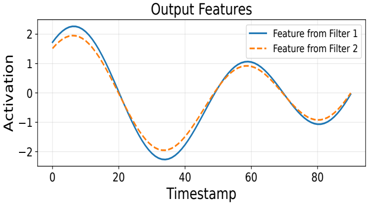

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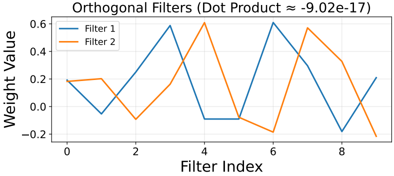

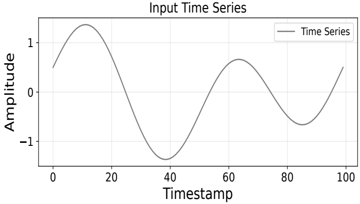

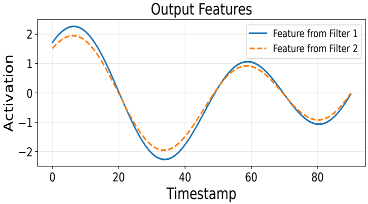

- In this work, we impose diversity constraints on features.

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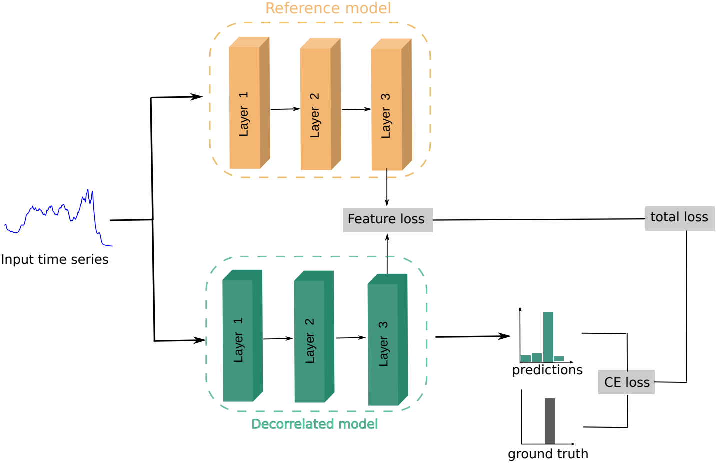
Proposed Approach

Overview of our Diversity Driven Decorrelated Learning Approach



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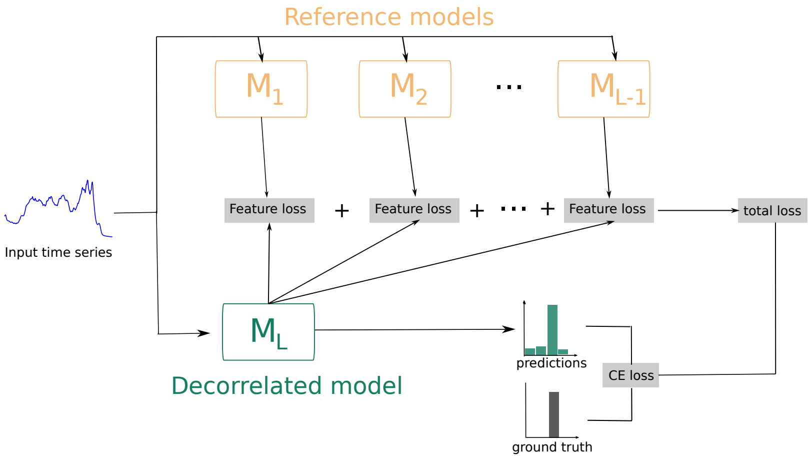

Diversity Loss Formulation

- We propose a diversity loss that encourages orthogonality between feature maps:

$$L_{orth} = \sum_{i \neq j} \left| \frac{\mathbf{F}_{deco,i} \cdot \mathbf{F}_{base,j}^{\top}}{|\mathbf{F}_{deco,i}||\mathbf{F}_{base,j}|} \right| \tag{1}$$

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- Combined with standard classification loss:

$$L_{total} = \alpha L_{class} + (1 - \alpha) L_{orth} \tag{2}$$

where α controls the balance

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Experimental Setup

- **Baseline model:** LITETime

Reference:
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- **Datasets:** University California Riverside (UCR) archive 2018
  - We use 128 univariate time series datasets
  - All datasets already split into train and test sets

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- **Baseline model:** LITETime
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- **Performance Comparison**
  - We compared standard LITETime ensembles with their decorrelated counterparts (Deco-LITETime), focusing on ensemble configurations ranging from 2 to 5 models.

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  - We compared standard LITETime ensembles with their decorrelated counterparts (Deco-LITETime), focusing on ensemble configurations ranging from 2 to 5 models.
- **Metrics**
  - Ensemble accuracy of models are compared for each dataset from the UCR archive
  - Number of wins, ties and losses are computed for comparing models

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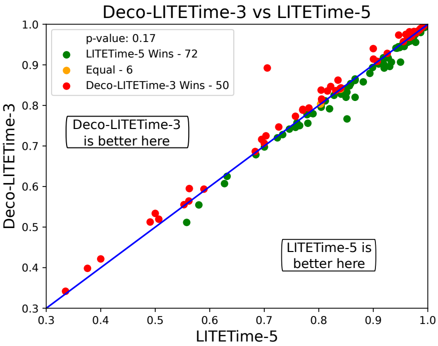
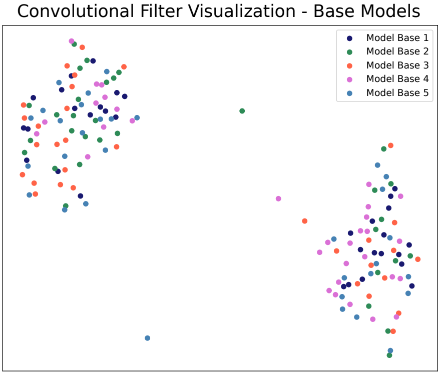
Performance Comparison

- ▷ 40% smaller *Deco-LITETime-3* achieves state-of-the-art performance as *LITETime-5*

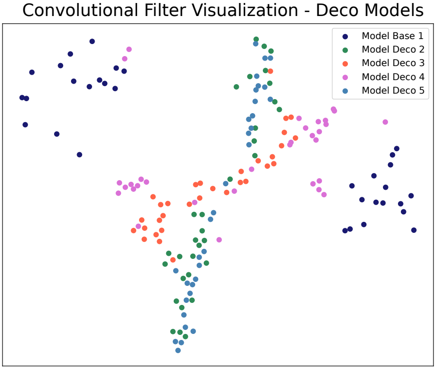


Qualitative Diversity Analysis

- Visualizated convolutional filters form *base* and *decorrelated* models
- The t-SNE technique was employed to reduce the dimensionality of the filters for visualization



(a) Filters from base models

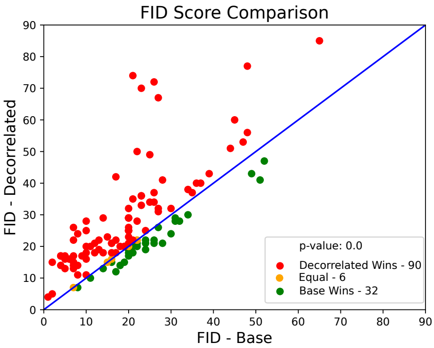


(b) Filters from decorrelated models

Quantitative Diversity Analysis

- We use the Fréchet Inception Distance (FID) to quantitatively assess the diversity between feature outputs.
- The FID score compares:

  x-axis: Between two base models (Base_1 vs Base_2)
  y-axis: Between a base model and a decorrelated model (Base_1 vs Decorrelated_2)



FID comparison plot showing the effect of decorrelation on feature diversity.

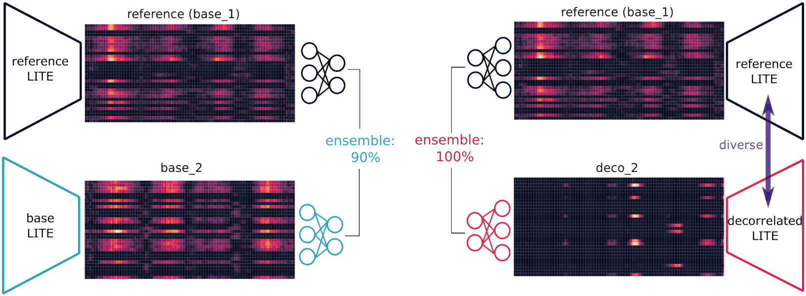
Takeaway

- ▷ We proposed Diversity Driven Ensemble Learning approach for TSC tasks
- ▷ Our approach, achieves state-of-the-art performance with 40% less parameters than the baseline LITETime model
- ▷ A current limitation is that the ensemble learning process is sequential
- ▷ As a perspective, in future work we plan to explore parallelizing the ensemble training

Code available here: https://github.com/MSD-IRIMAS/decorrelated-learning

Contact: https://javidanabdullayev.github.io/

Feature Diversity



Comparison of ensemble model performances and feature maps on the BirdChicken dataset, from standard and decorrelated training.

Performance Comparison

The Multi-Comparison Matrix illustrates performance of each decorrelated and base ensemble variants in one-vs-one comparisons.

Mean-Accuracy	Deco-LITETime-4 0.8496	Deco-LITETime-5 0.8494	LITETime-5 0.8472	Deco-LITETime-3 0.8469	LITETime-4 0.8463	LITETime-3 0.8455	LITETime-2 0.8431	Deco-LITETime-2 0.8427
Deco-LITETime-4 0.8496	Mean-Difference r>c / r=c / r<c Wilcoxon p-value	0.0002 44 / 20 / 64 0.2862	0.0025 59 / 8 / 61 0.5721	**0.0028 81 / 13 / 34 ≤ 1e-04**	**0.0033 68 / 9 / 51 0.0492**	**0.0041 73 / 13 / 42 0.0012**	**0.0066 85 / 10 / 33 ≤ 1e-04**	**0.0069 94 / 11 / 23 ≤ 1e-04**
Deco-LITETime-5 0.8494	-0.0002 64 / 20 / 44 0.2862	-	0.0023 62 / 9 / 57 0.2409	**0.0026 83 / 13 / 32 ≤ 1e-04**	**0.0031 71 / 8 / 49 0.0136**	**0.0039 75 / 12 / 41 0.0005**	**0.0064 85 / 10 / 33 ≤ 1e-04**	**0.0067 94 / 10 / 24 ≤ 1e-04**
LITETime-5 0.8472	-0.0025 61 / 8 / 59 0.5721	-0.0023 57 / 9 / 62 0.2409	-	0.0003 72 / 6 / 50 0.1718	**0.0009 68 / 27 / 33 0.0016**	**0.0017 78 / 14 / 36 0.0002**	**0.0041 88 / 13 / 27 ≤ 1e-04**	**0.0045 89 / 6 / 33 ≤ 1e-04**
Deco-LITETime-3 0.8469	**-0.0028 34 / 13 / 81 ≤ 1e-04**	**-0.0026 32 / 13 / 83 ≤ 1e-04**	-0.0003 50 / 6 / 72 0.1718	-	0.0006 54 / 6 / 68 0.5387	0.0014 60 / 7 / 61 0.6419	**0.0038 74 / 11 / 43 0.0012**	**0.0042 89 / 8 / 31 ≤ 1e-04**
Deco-LITETime-2 0.8427	**-0.0069 23 / 11 / 94 ≤ 1e-04**	**-0.0067 24 / 10 / 94 ≤ 1e-04**	**-0.0045 33 / 6 / 89 ≤ 1e-04**	**-0.0042 31 / 8 / 89 ≤ 1e-04**	**-0.0036 39 / 7 / 82 0.0002**	**-0.0028 40 / 6 / 82 0.0007**	-0.0004 58 / 6 / 64 0.4763	**If in bold, then p-value < 0.05**

Mean-Difference: 0.0075, 0.0050, 0.0025, 0.0000, −0.0025, −0.0050, −0.0075

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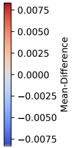

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Deco-LITETime-3 0.8469	**-0.0028 34 / 13 / 81 ≤ 1e-04**	**-0.0026 32 / 13 / 83 ≤ 1e-04**	-0.0003 50 / 6 / 72 0.1718	-	0.0006 54 / 6 / 68 0.5387	0.0014 60 / 7 / 61 0.6419	**0.0038 74 / 11 / 43 0.0012**	**0.0042 89 / 8 / 31 ≤ 1e-04**
Deco-LITETime-2 0.8427	**-0.0069 23 / 11 / 94 ≤ 1e-04**	**-0.0067 24 / 10 / 94 ≤ 1e-04**	**-0.0045 33 / 6 / 89 ≤ 1e-04**	**-0.0042 31 / 8 / 89 ≤ 1e-04**	**-0.0036 39 / 7 / 82 0.0002**	**-0.0028 40 / 6 / 82 0.0007**	-0.0004 58 / 6 / 64 0.4763	**If in bold, then p-value < 0.05**

Mean-Difference: 0.0075, 0.0050, 0.0025, 0.0000, −0.0025, −0.0050, −0.0075

Performance Comparison

The Multi-Comparison Matrix illustrates performance of each decorrelated and base ensemble variants in one-vs-one comparisons.

Mean-Accuracy	Deco-LITETime-4 0.8496	Deco-LITETime-5 0.8494	LITETime-5 0.8472	Deco-LITETime-3 0.8469	LITETime-4 0.8463	LITETime-3 0.8455	LITETime-2 0.8431	Deco-LITETime-2 0.8427
Deco-LITETime-4 0.8496	Mean-Difference r>c / r=c / r<c Wilcoxon p-value	0.0002 44 / 20 / 64 0.2862	0.0025 59 / 8 / 61 0.5721	**0.0028 81 / 13 / 34 ≤ 1e-04**	**0.0033 68 / 9 / 51 0.0492**	**0.0041 73 / 13 / 42 0.0012**	**0.0066 85 / 10 / 33 ≤ 1e-04**	**0.0069 94 / 11 / 23 ≤ 1e-04**
Deco-LITETime-5 0.8494	-0.0002 64 / 20 / 44 0.2862	-	0.0023 62 / 9 / 57 0.2409	**0.0026 83 / 13 / 32 ≤ 1e-04**	**0.0031 71 / 8 / 49 0.0136**	**0.0039 75 / 12 / 41 0.0005**	**0.0064 85 / 10 / 33 ≤ 1e-04**	**0.0067 94 / 10 / 24 ≤ 1e-04**
LITETime-5 0.8472	-0.0025 61 / 8 / 59 0.5721	-0.0023 57 / 9 / 62 0.2409	-	0.0003 72 / 6 / 50 0.1718	**0.0009 68 / 27 / 33 0.0016**	**0.0017 78 / 14 / 36 0.0002**	**0.0041 88 / 13 / 27 ≤ 1e-04**	**0.0045 89 / 6 / 33 ≤ 1e-04**
Deco-LITETime-3 0.8469	**-0.0028 34 / 13 / 81 ≤ 1e-04**	**-0.0026 32 / 13 / 83 ≤ 1e-04**	-0.0003 50 / 6 / 72 0.1718	-	0.0006 54 / 6 / 68 0.5387	0.0014 60 / 7 / 61 0.6419	**0.0038 74 / 11 / 43 0.0012**	**0.0042 89 / 8 / 31 ≤ 1e-04**
Deco-LITETime-2 0.8427	**-0.0069 23 / 11 / 94 ≤ 1e-04**	**-0.0067 24 / 10 / 94 ≤ 1e-04**	**-0.0045 33 / 6 / 89 ≤ 1e-04**	**-0.0042 31 / 8 / 89 ≤ 1e-04**	**-0.0036 39 / 7 / 82 0.0002**	**-0.0028 40 / 6 / 82 0.0007**	-0.0004 58 / 6 / 64 0.4763	**If in bold, then p-value < 0.05**

Mean-Difference: 0.0075, 0.0050, 0.0025, 0.0000, −0.0025, −0.0050, −0.0075

Performance Comparison

The Multi-Comparison Matrix illustrates performance of each decorrelated and base ensemble variants in one-vs-one comparisons.

Mean-Accuracy	Deco-LITETime-4 0.8496	Deco-LITETime-5 0.8494	LITETime-5 0.8472	Deco-LITETime-3 0.8469	LITETime-4 0.8463	LITETime-3 0.8455	LITETime-2 0.8431	Deco-LITETime-2 0.8427
Deco-LITETime-4 0.8496	Mean-Difference r>c / r=c / r<c Wilcoxon p-value	0.0002 44 / 20 / 64 0.2862	0.0025 59 / 8 / 61 0.5721	**0.0028** **81 / 13 / 34** **≤ 1e-04**	**0.0033** **68 / 9 / 51** **0.0492**	**0.0041** **73 / 13 / 42** **0.0012**	**0.0066** **85 / 10 / 33** **≤ 1e-04**	**0.0069** **94 / 11 / 23** **≤ 1e-04**
Deco-LITETime-5 0.8494	-0.0002 64 / 20 / 44 0.2862	-	0.0023 62 / 9 / 57 0.2409	**0.0026** **83 / 13 / 32** **≤ 1e-04**	**0.0031** **71 / 8 / 49** **0.0136**	**0.0039** **75 / 12 / 41** **0.0005**	**0.0064** **85 / 10 / 33** **≤ 1e-04**	**0.0067** **94 / 10 / 24** **≤ 1e-04**
LITETime-5 0.8472	-0.0025 61 / 8 / 59 0.5721	-0.0023 57 / 9 / 62 0.2409	-	0.0003 72 / 6 / 50 0.1718	**0.0009** **68 / 27 / 33** **0.0016**	**0.0017** **78 / 14 / 36** **0.0002**	**0.0041** **88 / 13 / 27** **≤ 1e-04**	**0.0045** **89 / 6 / 33** **≤ 1e-04**
Deco-LITETime-3 0.8469	**-0.0028** **34 / 13 / 81** **≤ 1e-04**	**-0.0026** **32 / 13 / 83** **≤ 1e-04**	-0.0003 50 / 6 / 72 0.1718	-	0.0006 54 / 6 / 68 0.5387	0.0014 60 / 7 / 61 0.6419	**0.0038** **74 / 11 / 43** **0.0012**	**0.0042** **89 / 8 / 31** **≤ 1e-04**
Deco-LITETime-2 0.8427	**-0.0069** **23 / 11 / 94** **≤ 1e-04**	**-0.0067** **24 / 10 / 94** **≤ 1e-04**	**-0.0045** **33 / 6 / 89** **≤ 1e-04**	**-0.0042** **31 / 8 / 89** **≤ 1e-04**	**-0.0036** **39 / 7 / 82** **0.0002**	**-0.0028** **40 / 6 / 82** **0.0007**	-0.0004 58 / 6 / 64 0.4763	**If in bold, then** **p-value < 0.05**

Mean-Difference: 0.0075, 0.0050, 0.0025, 0.0000, −0.0025, −0.0050, −0.0075