Remote Sensing Time Series as Covariance Matrices for Crop Classification

Master Thesis Defense

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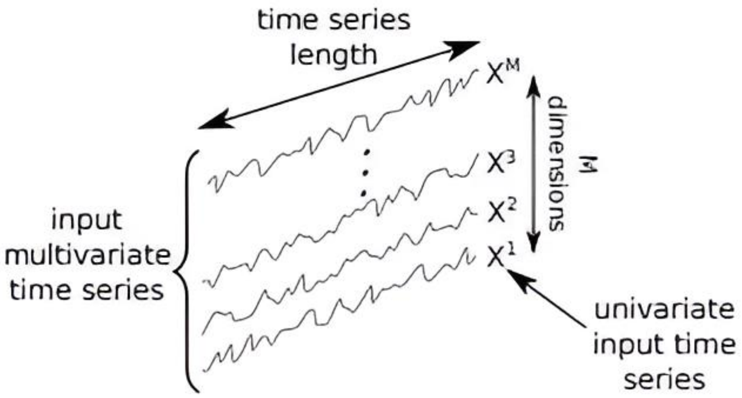
Introduction



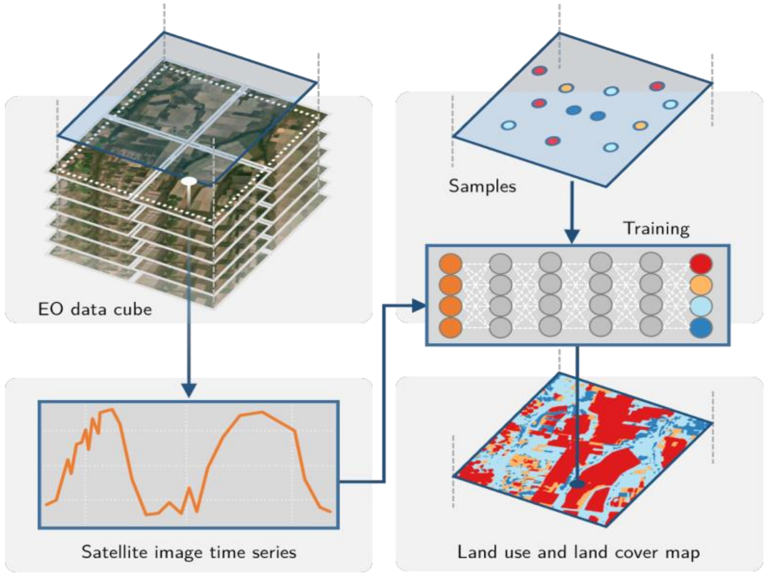
Representation of multi-variate TS. Source: Akodad, S., 2021

$$\{(\boldsymbol{X}_1, y_1), (\boldsymbol{X}_2, y_2), \ldots, (\boldsymbol{X}_n, y_n)\}$$

$$X_k = (x_i^1, x_i^2, \ldots, x_i^T)_{i=1}^q$$

- Large timeseries (TS) of **multi-spectral** images.
- Captures **spectral** information across multiple wavelengths across a finite **temporal** sequence.

Supervised learning task for crop classification using remote sensing TS data through second-order statistics, specifically **covariance matrices**.



Example of SITS. Source: Intro to SITS

Motivations

In remote sensing TS, we have **high-dimensional data.**

With long sequences, we get **large data sizes.**

Limited labeled sample, and **irregular temporal sampling**, leading to **missing data**, particularly due to **cloud cover**.

Reliance on **first-order statistics**, which address the **global structure** but fail to capture **local intricacies**.

Objectives

Following the classical manifold learning theory, **learning** or **preserving** the original data structure can enhance classification performance (Huang, Z. and Gool, L. V., 2016). We focus on the following research objectives:

1. Explore the unique **covariance representation** of remote sensing timeseries data to capture the **spectral-temporal** intricacies and dependencies.
2. Leveraging the underlying **Riemannian structure** of the data and engineer a state-of-the-art supervised learning algorithm.
3. Explore possible **variants** of the model with combinations of data representation.
4. Utilize **benchmark** datasets to evaluate the performance of the proposed models.

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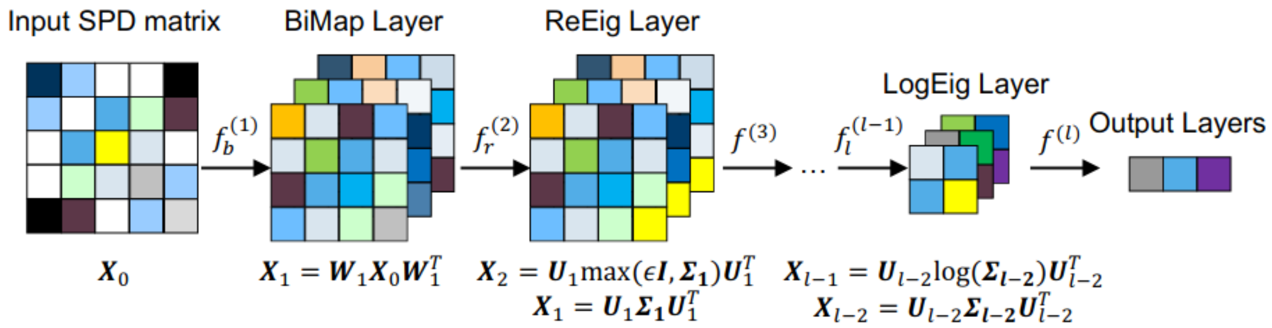
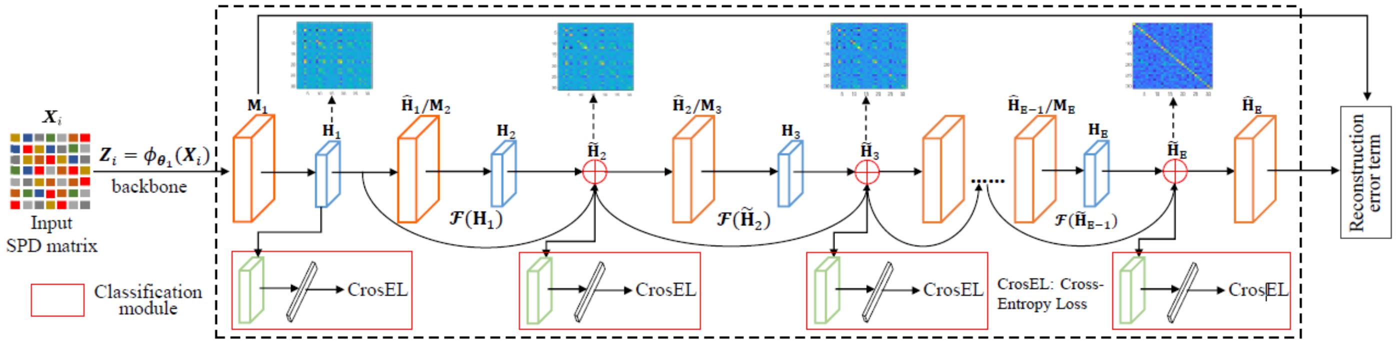
Riemannian Networks



Source: (Zhiwu Huang and Luc Van Gool, 2017)



Source: (Wang et.al, 2022)

SPDNet: A Riemannian Network

- SPDNet works on SPD matrices directly and exploits multiple layers tailored for SPD matrix deep learning.
- Our implementation is based on the foundational concept of this model.

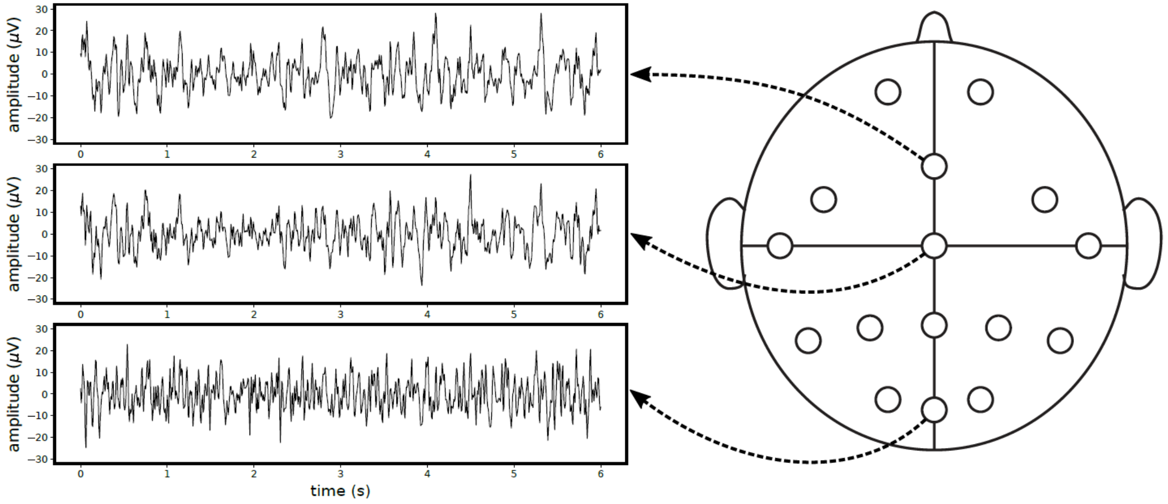
DreamNet: A Stacked Riemannian Autoencoder (SRAE) Network

- DreamNet implants several residual-like blocks using shortcut connections to augment the representational capacity of SRAE.

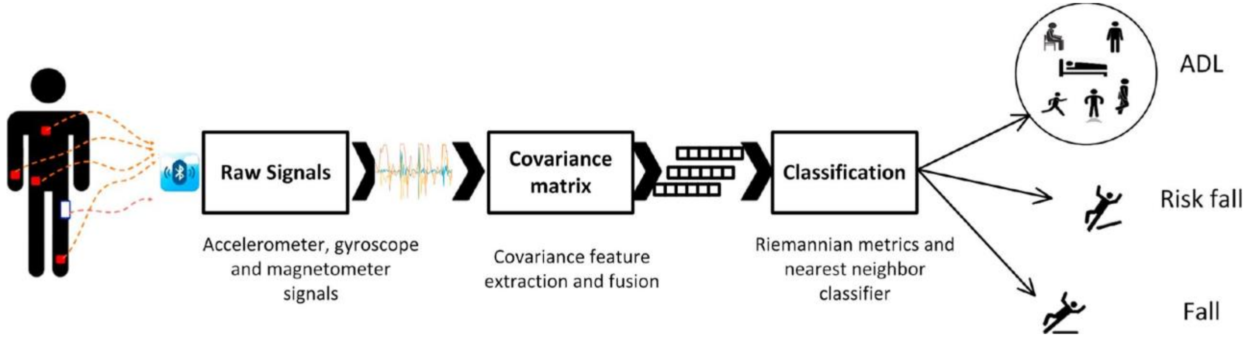
02

LITERATURE

Applications of Riemannian Approach



EEG classification. Source: (Pedro L. C. Rodrigues, 2019)



Fall detection from multiple wearable sensors. Source: (Bouetella, 2019)

- Brain Computer Interface (BCI) classification [1]
- Radar signals classification [2]
- Text, audio, and video classification [3]
- Stock market-state classification [4]

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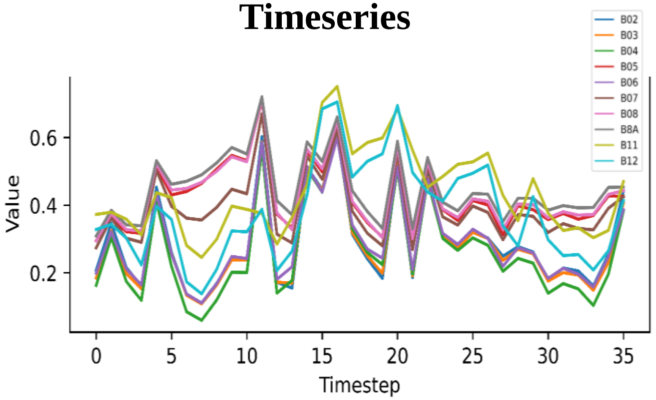
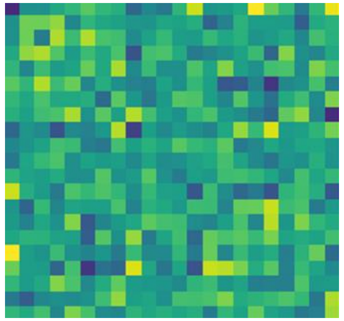
Methodology

Timeseries



Covariance



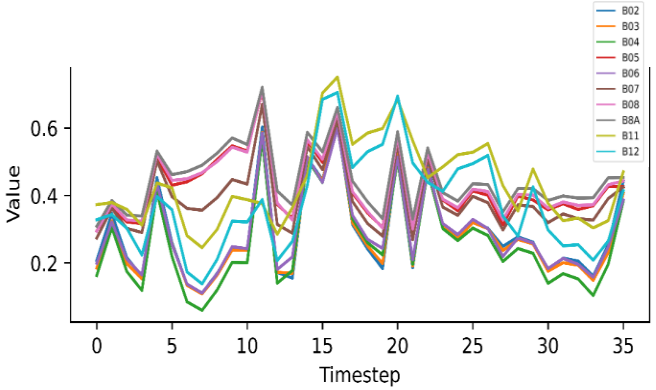
Processing

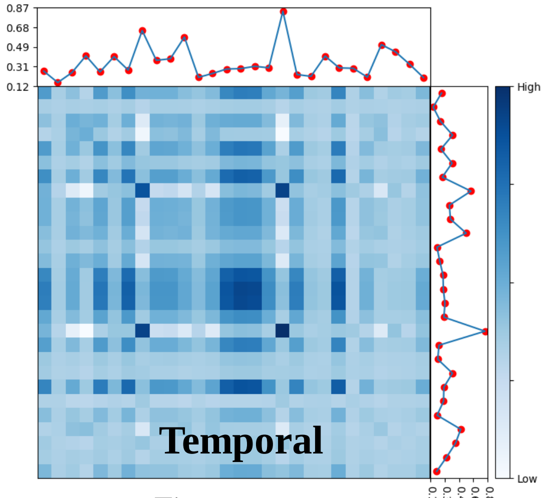
LERN MODEL

Crop class

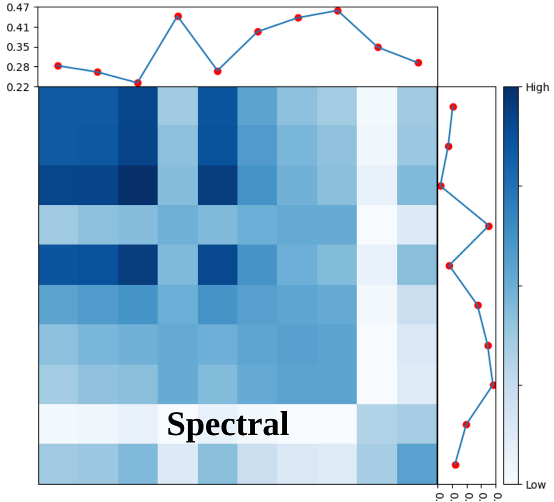
Winter Wheat
Source: [Dr. Erick J. Larson, 2013]

Covariance Estimation





Time sequence



Spectral bands

Sample Covariance Matrix

$$\boldsymbol{P} = \frac{1}{n-1}\sum_{i=1}^{n}(\boldsymbol{X}_i - \bar{\boldsymbol{X}})(\boldsymbol{X}_i - \bar{\boldsymbol{X}})^T$$

$$\boldsymbol{P} = \frac{1}{n-1}\sum_{i=1}^{n}(\boldsymbol{X}_i)(\boldsymbol{X}_i)^T$$

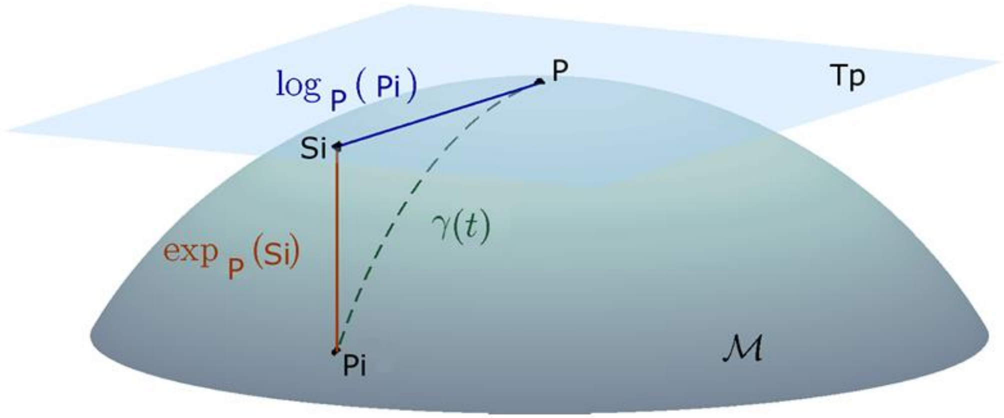
Regularization

$$\boldsymbol{P}_{reg} = \boldsymbol{P} + \epsilon \boldsymbol{I}$$

$$\boldsymbol{P}_{shrink} = (1-\alpha)\boldsymbol{P} + \alpha \boldsymbol{I}$$

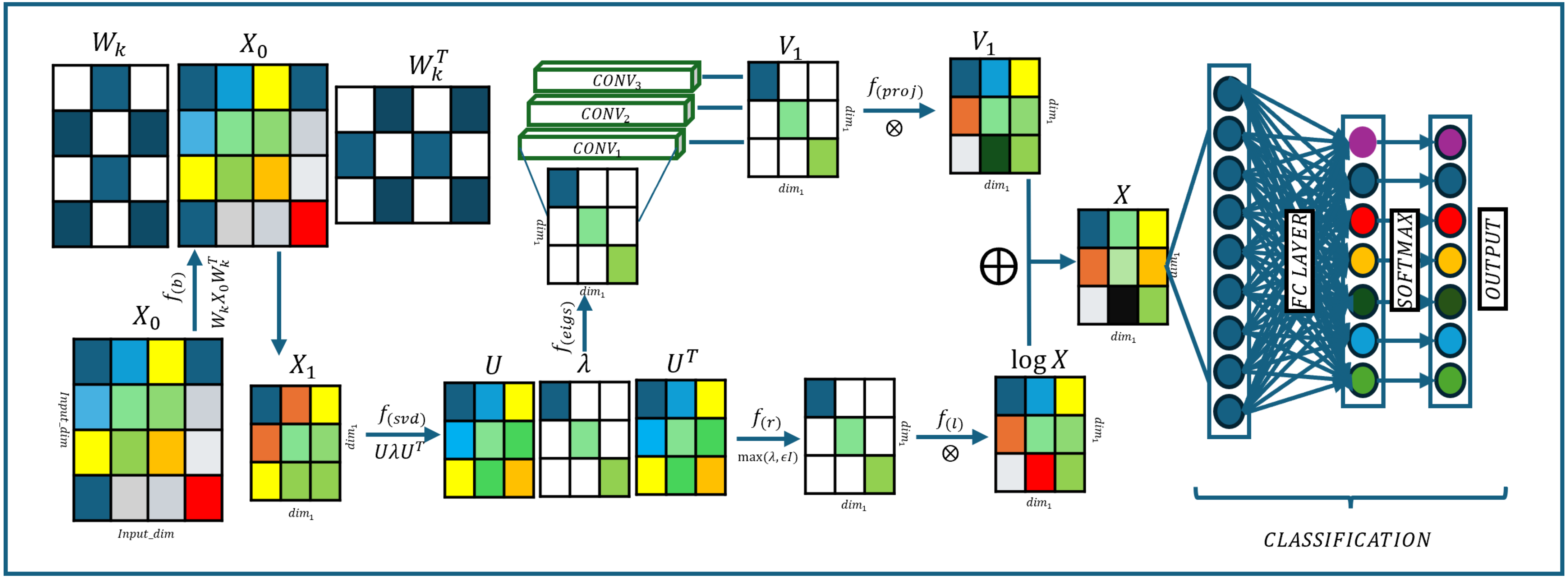
Covariance Matrix → SPD Matrix

- **Symmetric Positive Definite (SPD)**
  - $\boldsymbol{P} = \boldsymbol{P}^T$
  - Each $\boldsymbol{P}$ satisfies $x^T\boldsymbol{P}x > 0$ for all non-zero vectors $x \in \mathbb{R}^n$
- A **Riemannian manifold** $\mathcal{M}$ is a differentiable manifold, where the **tangent space**⇒ $T_P\mathcal{M}$ at each point P is a finite-dimensional Euclidean space.
- **SPD manifold** $S_+^d \in \mathcal{M}$ → $\boldsymbol{tangent\ space}$ ⇒ $T_P S_+^d$
- **Riemannian metric** ⇒ inner product: $g_p: T_p S_+^d \times T_p S_+^d \to \mathbb{R}$



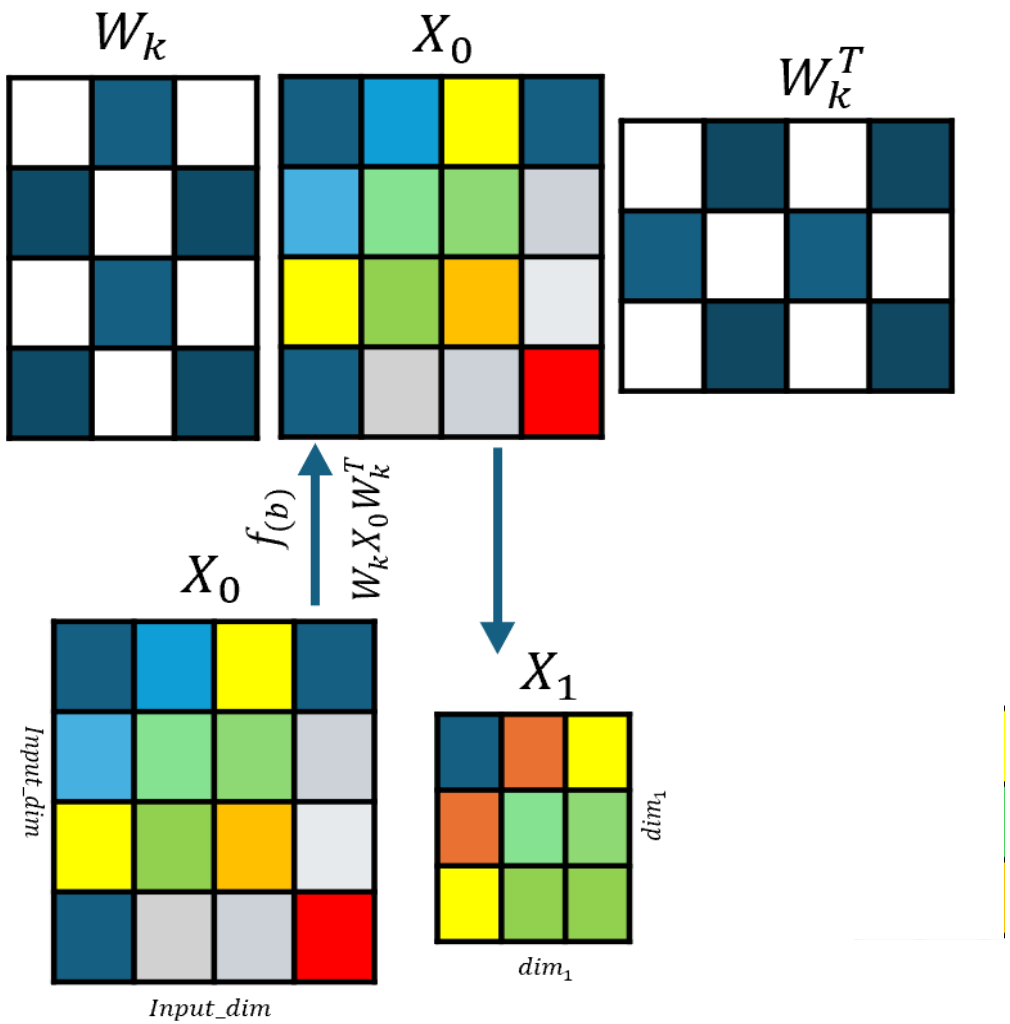
This represents the tangent space of the SPD manifold S_+^d at point P, where S_i the tangent vector of P_i and $\gamma(t)$ is the geodesic between P and P_i. Source: Barachant, A. et.al.

LogEucResNet (LERN) Model



Conceptual Diagram for LERN

First Block



BiMap Layer

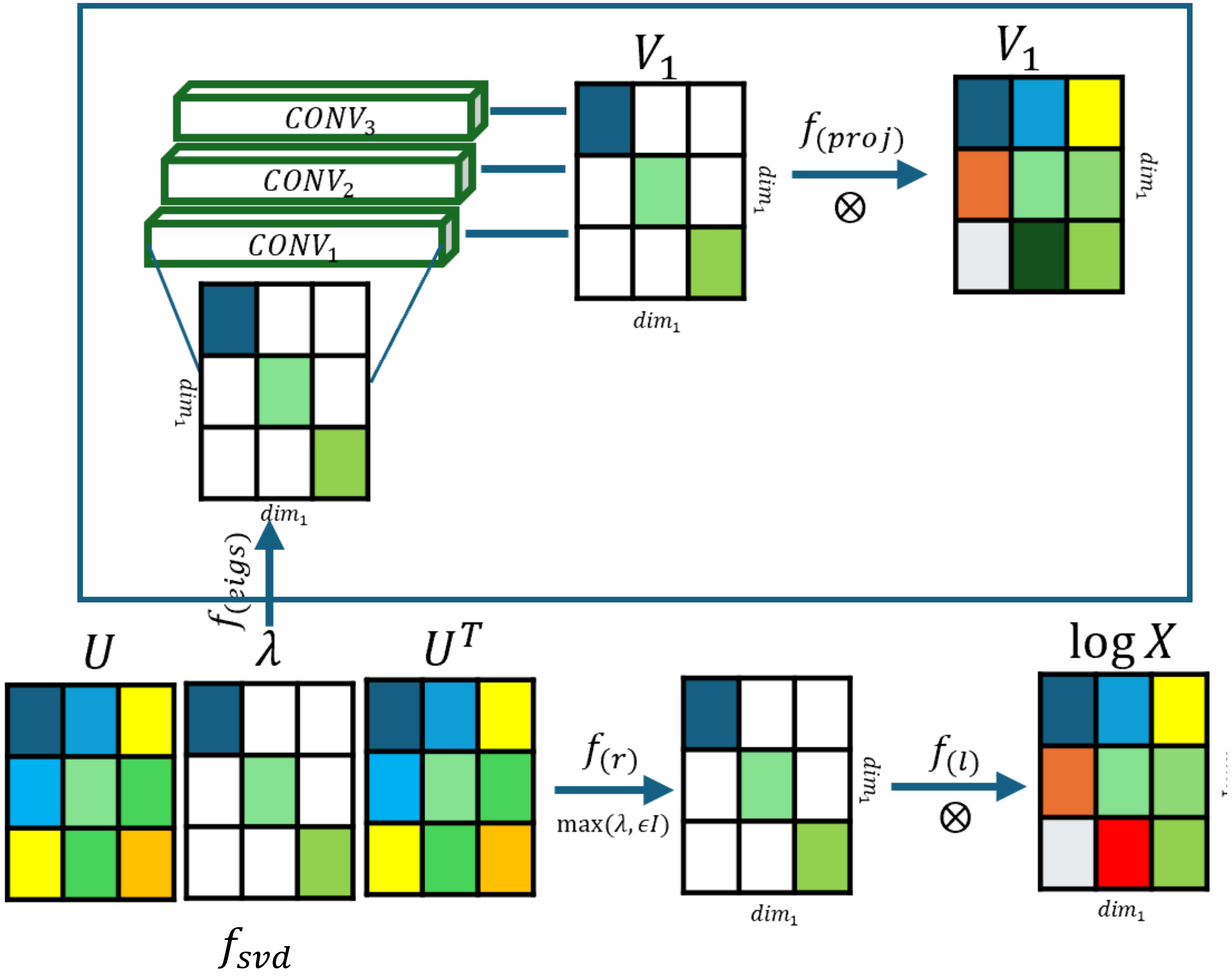
$$\boldsymbol{X}_k = f_{(b)}^{k}(\boldsymbol{X}_{k-1}, \boldsymbol{W}_k) = \boldsymbol{W}_k \boldsymbol{X}_{k-1} \boldsymbol{W}_k^T$$

- Input SPD matrices to new SPD matrices in a **sub-space.**
- **Reduce** dimension while preserving the **geometric structure** of the data.

Model Hyperparameter ⚠

$$\mathrm{dim}_1 = Bimap\ dimension$$

Second Block (a)



Single-Value Decomposition (SVD)

$$\boldsymbol{X}_k = f_{(svd)}^k (\boldsymbol{X}_{k-1}) = \boldsymbol{U}_{k-1} \boldsymbol{\lambda}_{k-1} \boldsymbol{U}_{k-1}^T$$

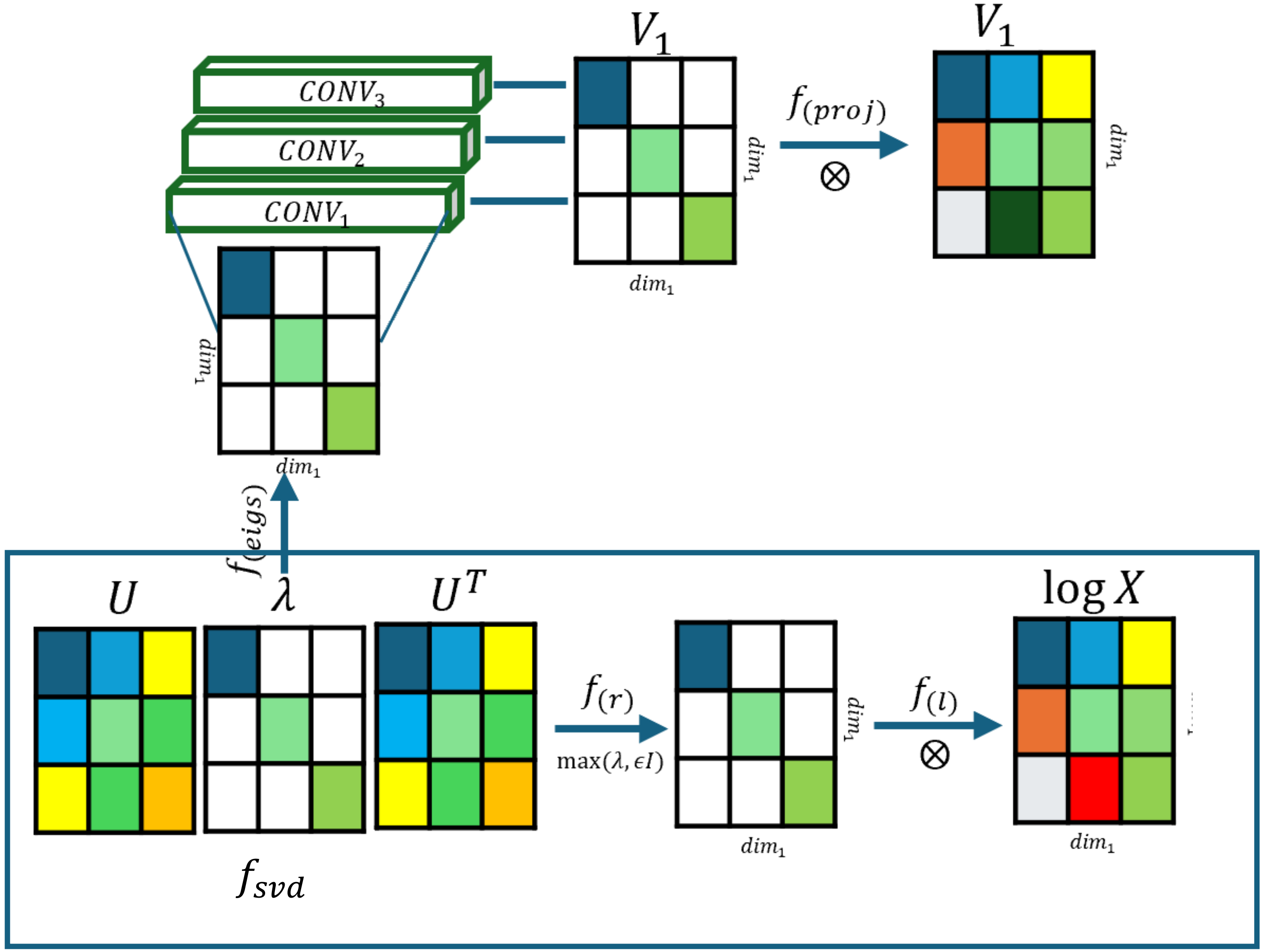
Spectrum Map

$$\widehat{\boldsymbol{v}} = f_{(eigs)}^k(\boldsymbol{\lambda}_{k-1})$$

Projection

$$\boldsymbol{v} = f_{(proj)}^k(\widehat{\boldsymbol{v}}) = \boldsymbol{P}\, \widehat{\boldsymbol{v}}\, \boldsymbol{P}^T$$

Second Block (b)



Single-Value Decomposition (SVD)

$$\boldsymbol{X}_k = f_{(svd)}^{k}(\boldsymbol{X}_{k-1}) = \boldsymbol{U}_{k-1}\,\boldsymbol{\lambda}_{k-1}\,\boldsymbol{U}_{k-1}^{T}$$

ReEig Layer

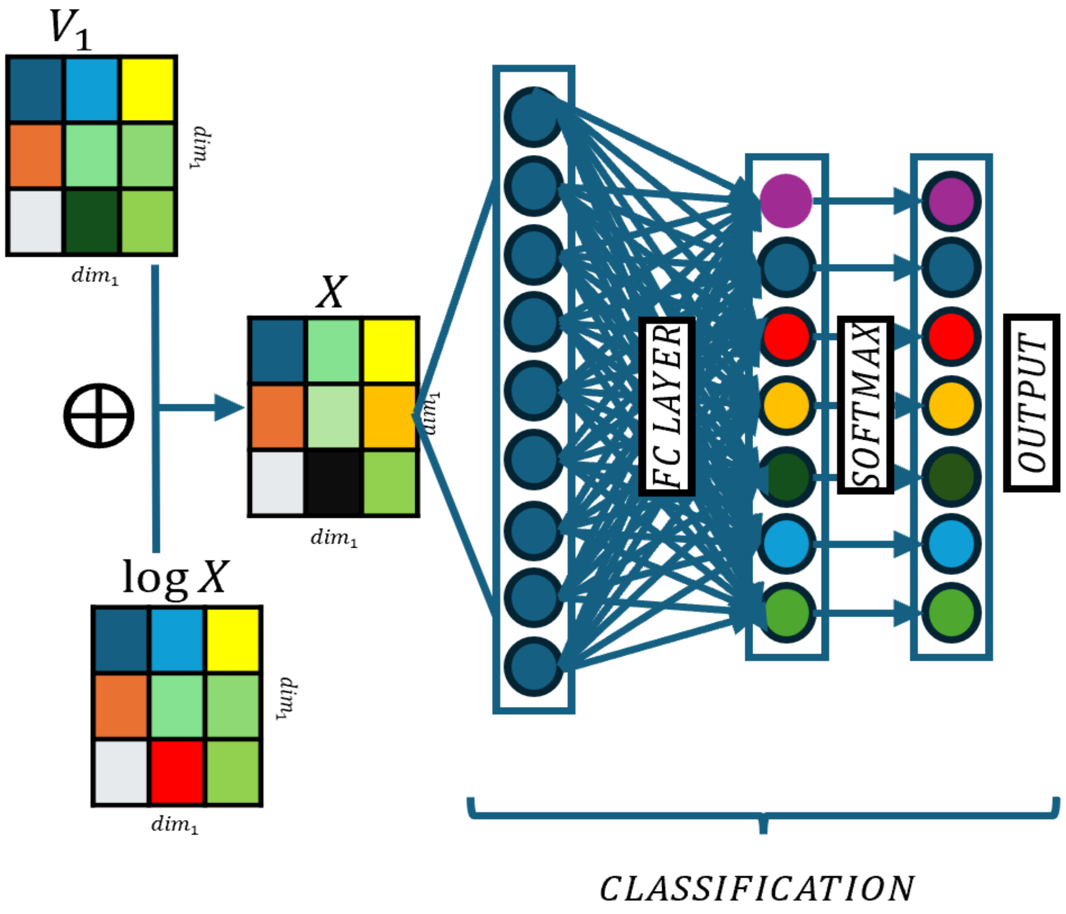
$$\boldsymbol{X}_k = f_{(r)}^{k}(\boldsymbol{X}_{k-1}) = \boldsymbol{U}_{k-1}\,\boldsymbol{max}(\boldsymbol{\lambda}_{k-1}, \epsilon\boldsymbol{I})\,\boldsymbol{U}_{k-1}^{T}$$

$$\boldsymbol{max}(\boldsymbol{\lambda}_{k-1}, \epsilon\boldsymbol{I}) = \begin{cases} \boldsymbol{\lambda}_{k-1}(i,i) & if \quad \boldsymbol{\lambda}_{k-1}(i,i) > \epsilon \\ \epsilon & if \quad \boldsymbol{\lambda}_{k-1}(i,i) \leq \epsilon \end{cases}$$

LogEig

$$\boldsymbol{X}_k = f_{(l)}^{k}(\boldsymbol{X}_{k-1}) = \boldsymbol{U}_{k-1}\,log(\boldsymbol{\lambda}_{k-1})\,\boldsymbol{U}_{k-1}^{T}$$

Third Block



Residual Block

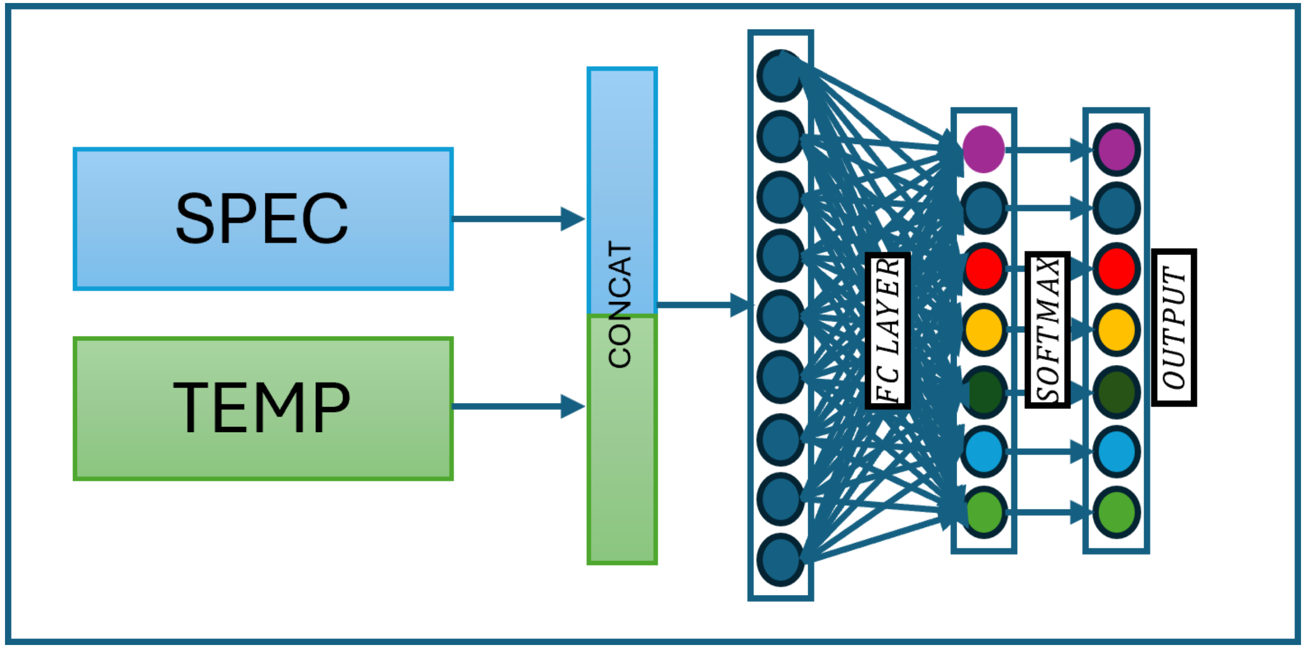
$$\boldsymbol{X} = \boldsymbol{X}_k \oplus \boldsymbol{v}$$

Classification Block

$$S_i = \log \boldsymbol{X} \cdot \text{proto}_i^T$$

$$D = \begin{bmatrix} S_1 \\ S_2 \\ \vdots \\ S_{n_{\text{proto}}} \end{bmatrix}$$

LERN - Combo



Conceptual Diagram for LERN-Combo

- This framework draws inspiration from the **Duplo** network by Interdonato, R., et.al (2019).
- **Fusing** two chains of networks OR sub-models
- Handle spectral and temporal covariance representations and captures distinct **patterns** and **features**

Loss Function

- **Focal Loss**

It was introduced by Lin et al. (2018), primarily designed for object detection to address class imbalance

$$\mathcal{L}_{\text{focal}} = -\alpha(1 - p_t)^{\gamma} \log(p_t)$$

α is **class weights**

γ is the **focusing parameter**

p_t is the model's **predicted probability**

Performance Metric

- **Weighted F-1 Score**

$$\text{F1-weighted} = \frac{1}{\sum_{i=1}^{n} N_i} \sum_{i=1}^{n} N_i \cdot \frac{2 \cdot \text{Precision}_i \cdot \text{Recall}_i}{\text{Precision}_i + \text{Recall}_i}$$

- **Macro F-1 Score**

$$\text{F1-macro} = \frac{1}{n} \sum_{i=1}^{n} \frac{2 \cdot \text{Precision}_i \cdot \text{Recall}_i}{\text{Precision}_i + \text{Recall}_i}$$

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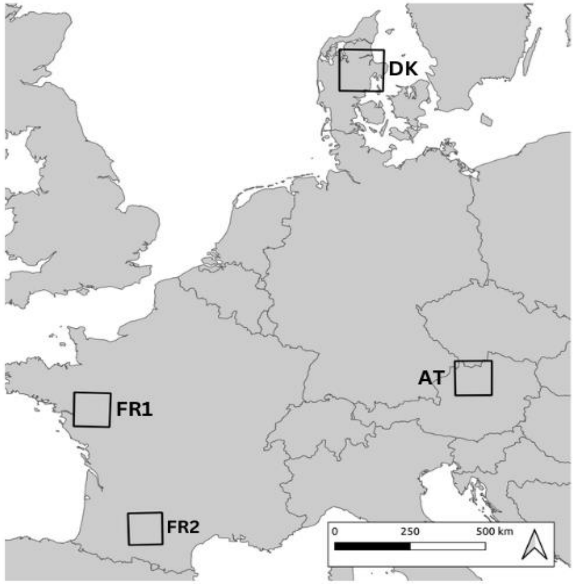
Datasets

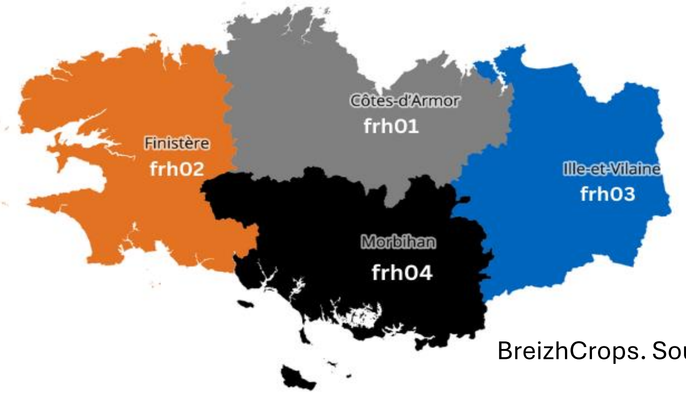
MiniTimeMatch → SITS for 4 regions across Europe
BreizhCrops → SITS for *Breizh* = *Bretagne* region

Table 1. Characteristics of the datasets

Region	# Observations	Bands	Sequence Length	# Classes
		MiniTimeMatch		
FR1	106,028	10	36	11
FR2	74,156	10	38	12
DK	53,823	10	28	12
AT	43,809	10	28	10
Total	**277,816**			
		BreizhCrops		
frh01	178,602	10	71	7
frh02	140,621	10	71	7
frh03	166,371	10	71	7
frh04	122,601	10	71	7
Total	**608,195**			



MiniTimeMatch. Source: link



BreizhCrops. Source: link

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Experiments

- **Default settings** with spectral-temporal covariance representations
- Manual **empirical hyperparameter tuning**
  - Bimap Layer Dimension
  - Gamma (γ) value
- Model evaluation with **optimal hyperparameters**
- Testing on **other regions**
- **Larger dataset** experimentation

Table 3. Initial configurations for the LERN models

Hyperparameter	**Value**
BiMap dim	$0.7 \times input_{dim}$
Number of Classes	11 (FR1 dataset)
Learning Rate (η)	10^{-2}
Batch Size	64
Epochs	200
Optimizer	RiemannianAdam
Scheduler	StepLr with step-size = 30
Loss function ($\mathcal{L}$)	Focal loss
Focusing parameter (γ)	2
Spectrum Map Parameters	Conv filter 10, 5, 1

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Results: MiniTimeMatch

MACRO F1-SCORE

Region	1-nn Log-Euc	1-nn Riem	CNN	LERN-Spec	LERN-Temp	LERN-Combo
AT	0.66	0.68	0.70	0.68	0.80	**0.81**
DK	0.56	0.64	0.51	0.54	0.61	**0.69**
FR1	0.63	0.65	0.78	0.71	0.78	**0.84**
FR2	0.59	0.64	0.61	0.63	0.67	**0.73**

WEIGHTED F1-SCORE

Region	1-nn Log-Euc	1-nn Riem	CNN	LERN-Spec	LERN-Temp	LERN-Combo
AT	0.90	0.91	**0.95**	0.93	0.94	**0.95**
DK	0.75	0.79	0.86	0.80	0.85	**0.89**
FR1	0.89	0.90	0.96	0.93	0.95	**0.97**
FR2	0.89	0.90	**0.95**	0.94	0.94	0.94

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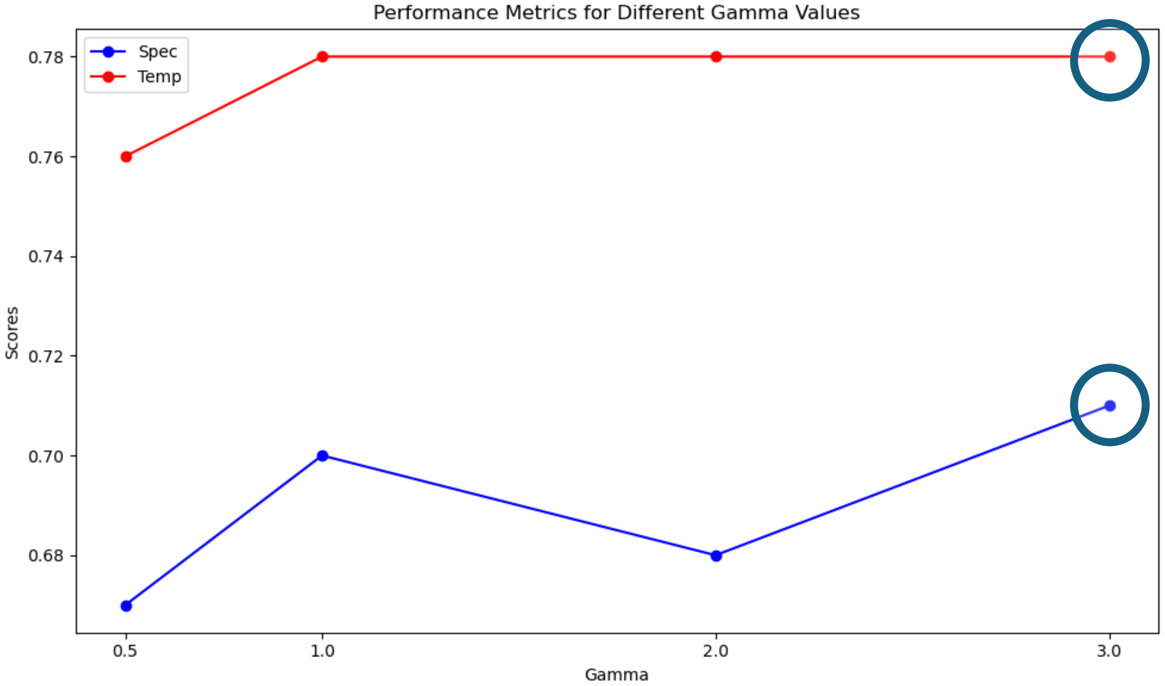
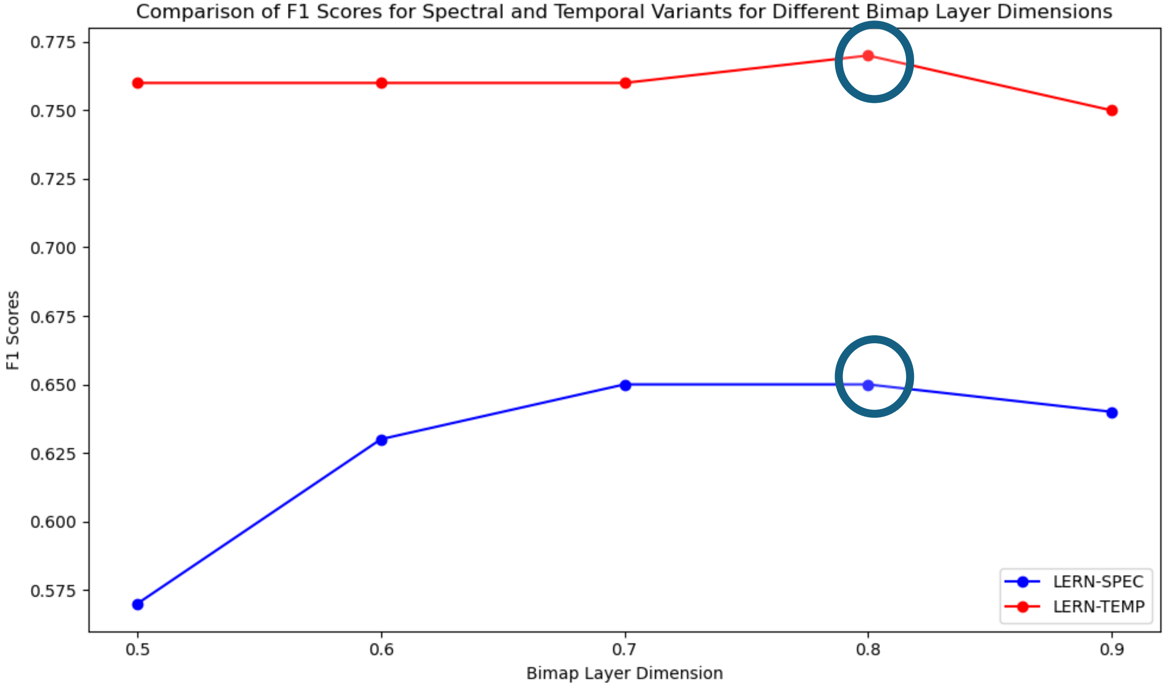
RESULTS

Optimal hyperparameters





Sensitivity of the model to its main hyperparameters

Optimal value

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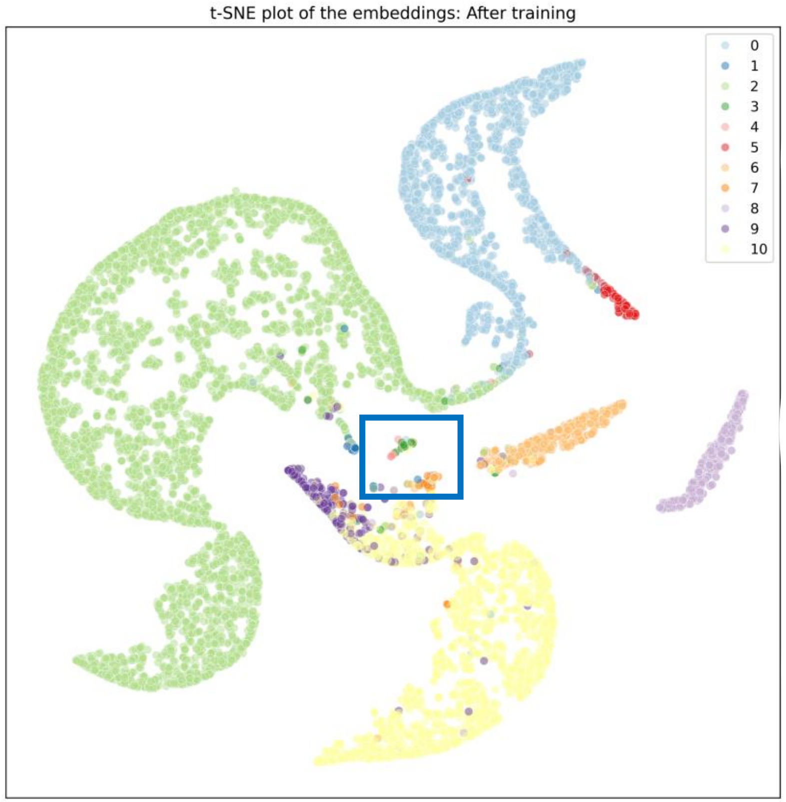
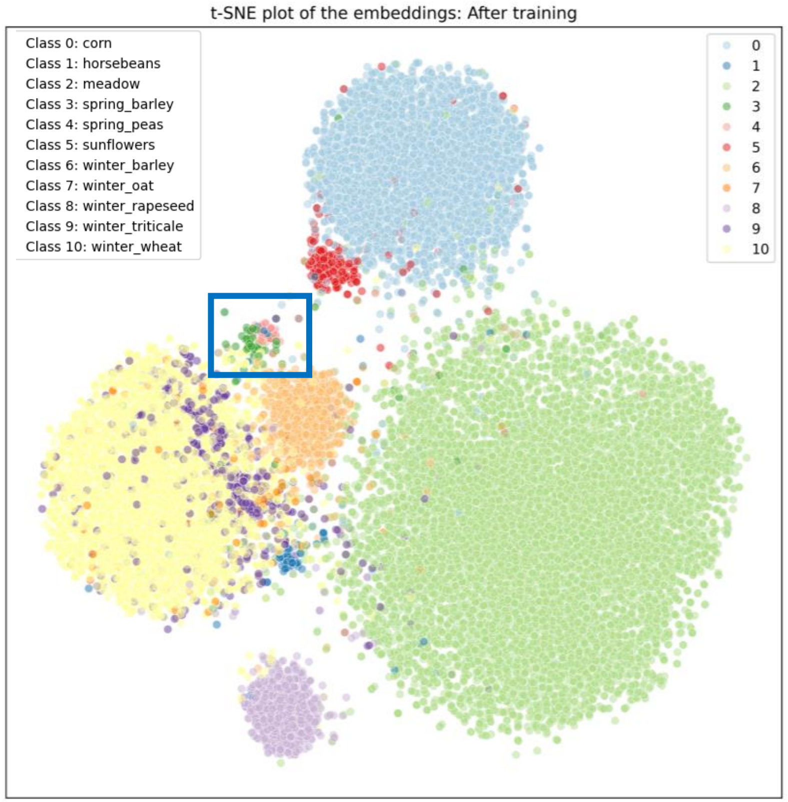
RESULTS

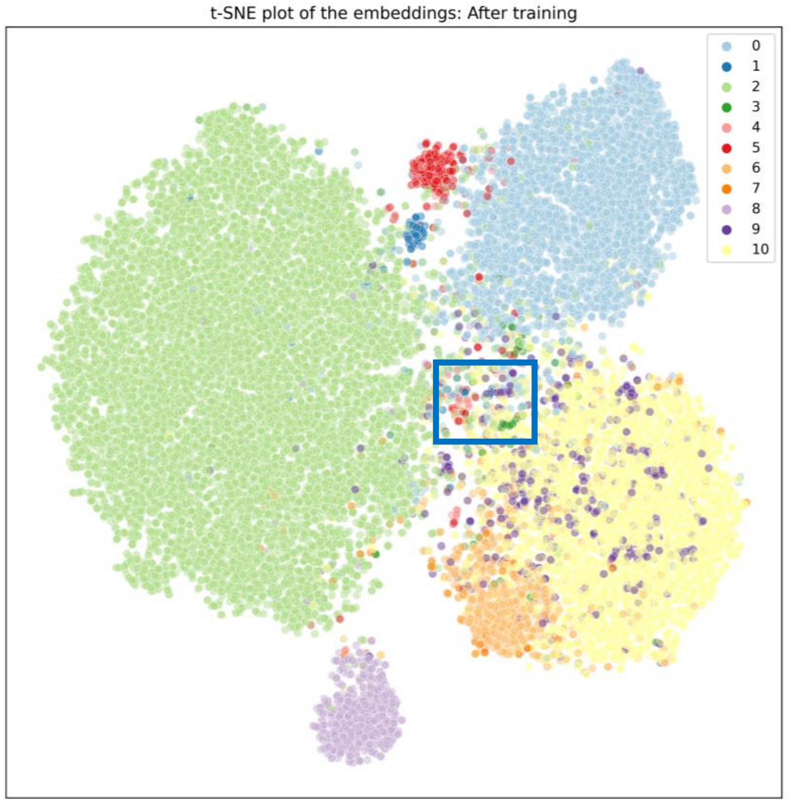
t-SNE plots for FR1



Combo output



Temp output



Spec output

Results: BreizhCrops

MACRO F1-SCORE

Region	1-nn Log-Euc	1-nn Riem	CNN	LERN-Spec	LERN-Temp	LERN-Combo
frh01	-	-	-	0.70	**0.76**	0.75
frh02	-	-	-	0.72	**0.77**	0.76
frh03	-	-	-	0.68	0.73	**0.74**
frh04	-	-	-	0.69	**0.74**	0.73

WEIGHTED F1-SCORE

Region	1-nn Log-Euc	1-nn Riem	CNN	LERN-Spec	LERN-Temp	LERN-Combo
frh01	-	-	-	0.79	**0.82**	**0.82**
frh02	-	-	-	0.77	0.80	**0.81**
frh03	-	-	-	0.76	0.78	**0.79**
frh04	-	-	-	0.75	0.78	**0.79**

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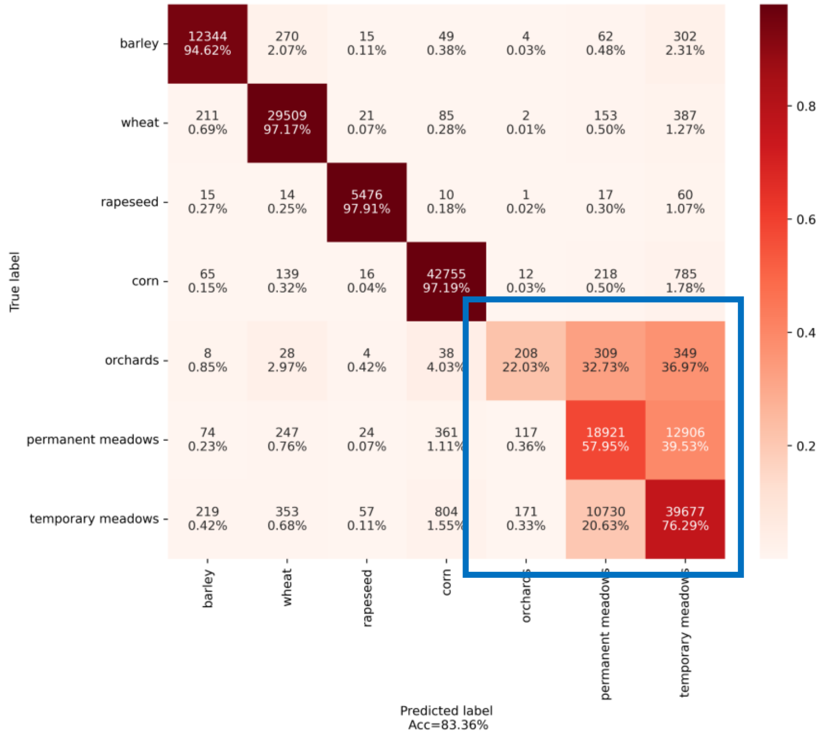
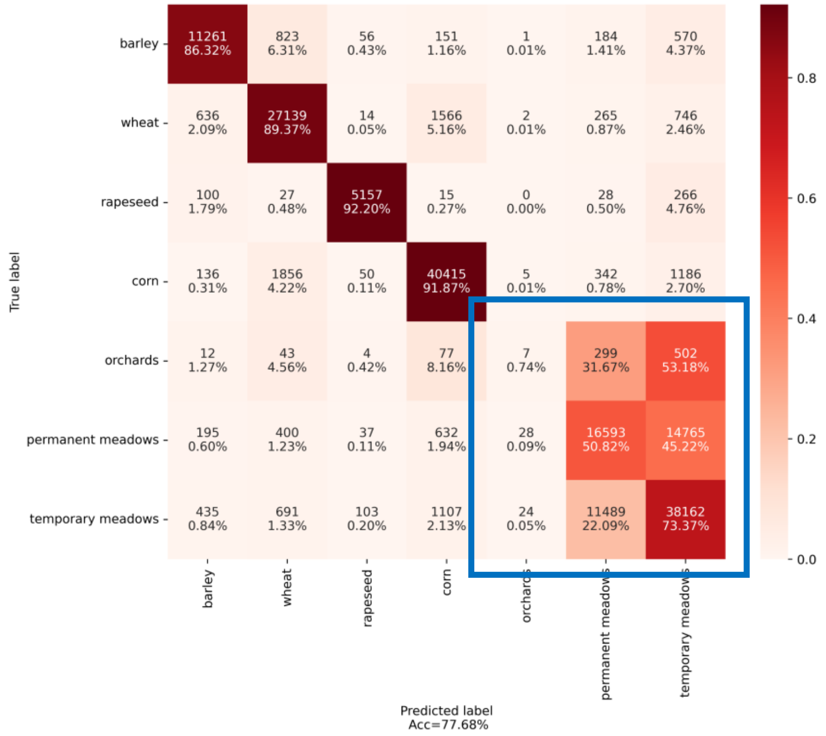
RESULTS

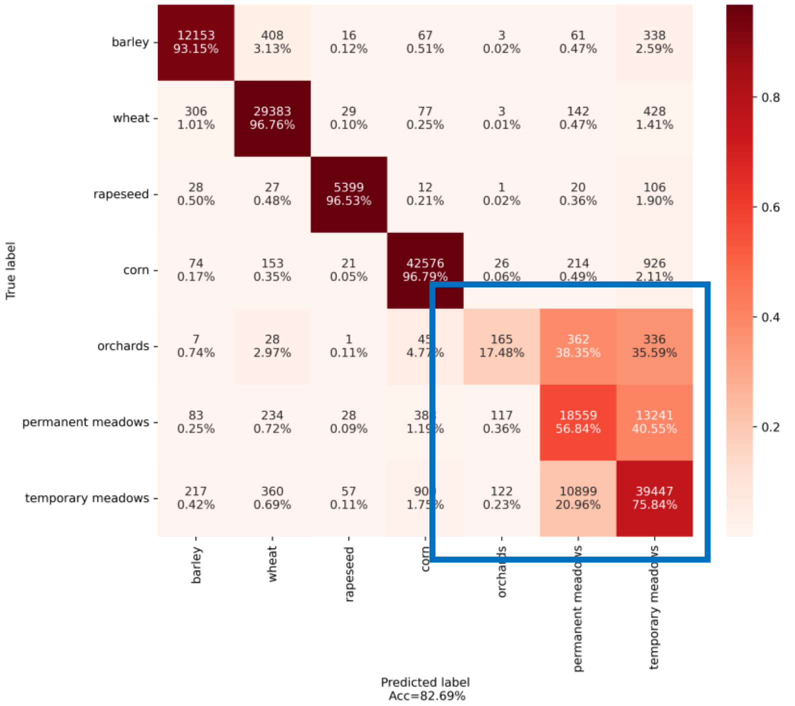
Breizhcrops



Combo output



Spec output



Temp output

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Conclusion

LERN-Combo > LERN-Temp > LERN-Spec

Introduced LERN & LERN-Combo: second-order geometry-aware neural network.

Utilized covariance representation for remote sensing timeseries data.

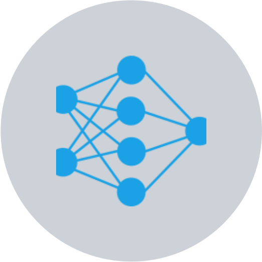
Embedded covariance matrices onto a Riemannian manifold using the LERN network.

Enhanced understanding and classification of complex timeseries patterns for crop classification.

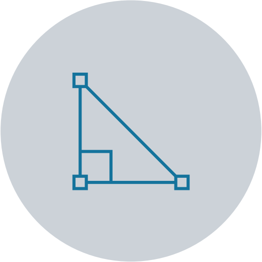
Challenges

- Sampling inhomogeneity
- SVD on high-dimensional matrices often computed on CPU only, making parallelization difficult.
- Dataset imbalances
- Spectral similarities
- High computational demands, particularly for matrix operations

Future Perspectives



EXPLORE ARCHITECTURAL HYPERPARAMETERS



RIEMANNIAN BATCH NORMALIZATION (RBN)

STATISTICAL SIGNIFICANCE TESTS

CLASS-SPECIFIC ANALYSIS

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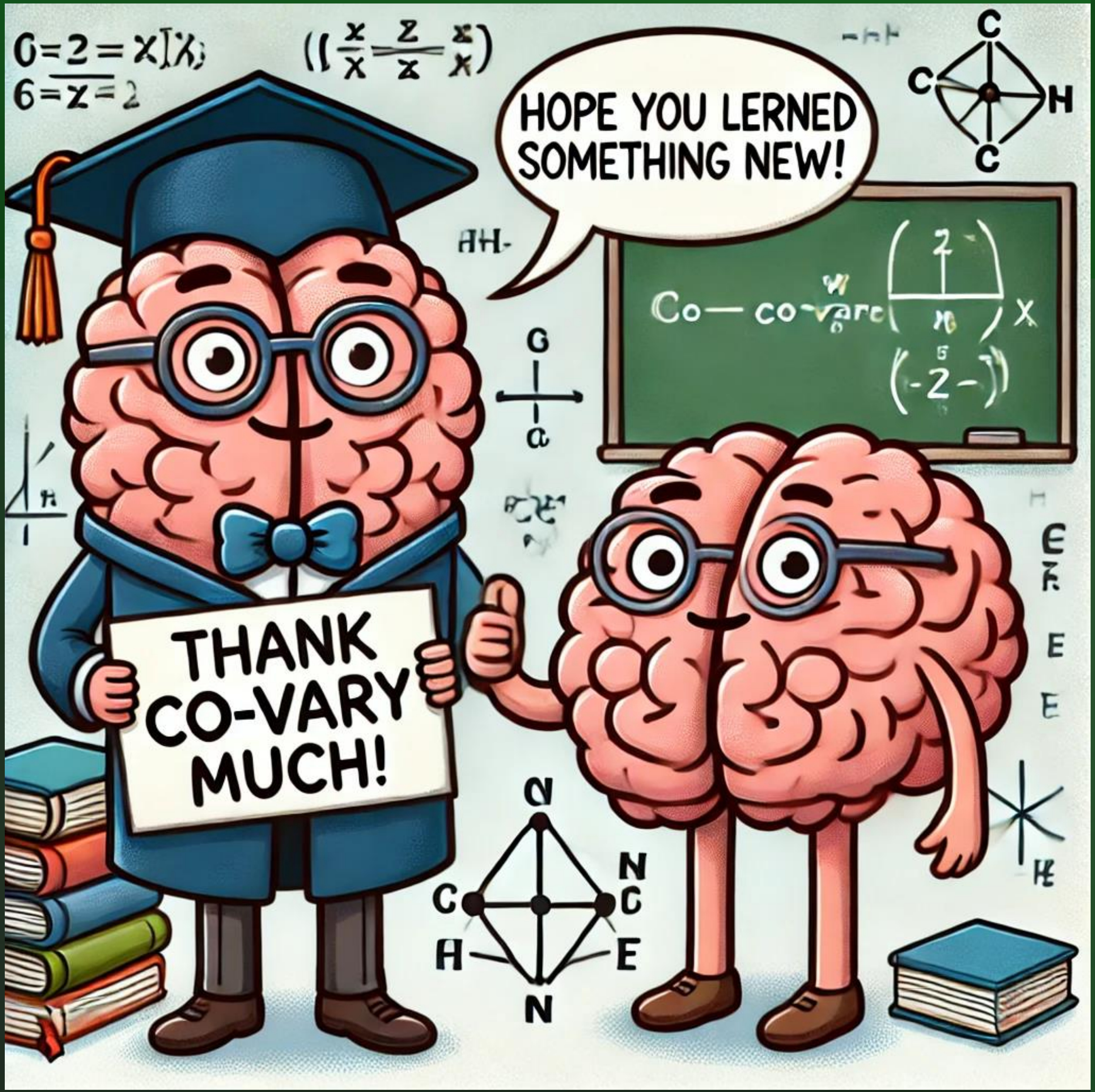


Made with ChatGPT

Appendix

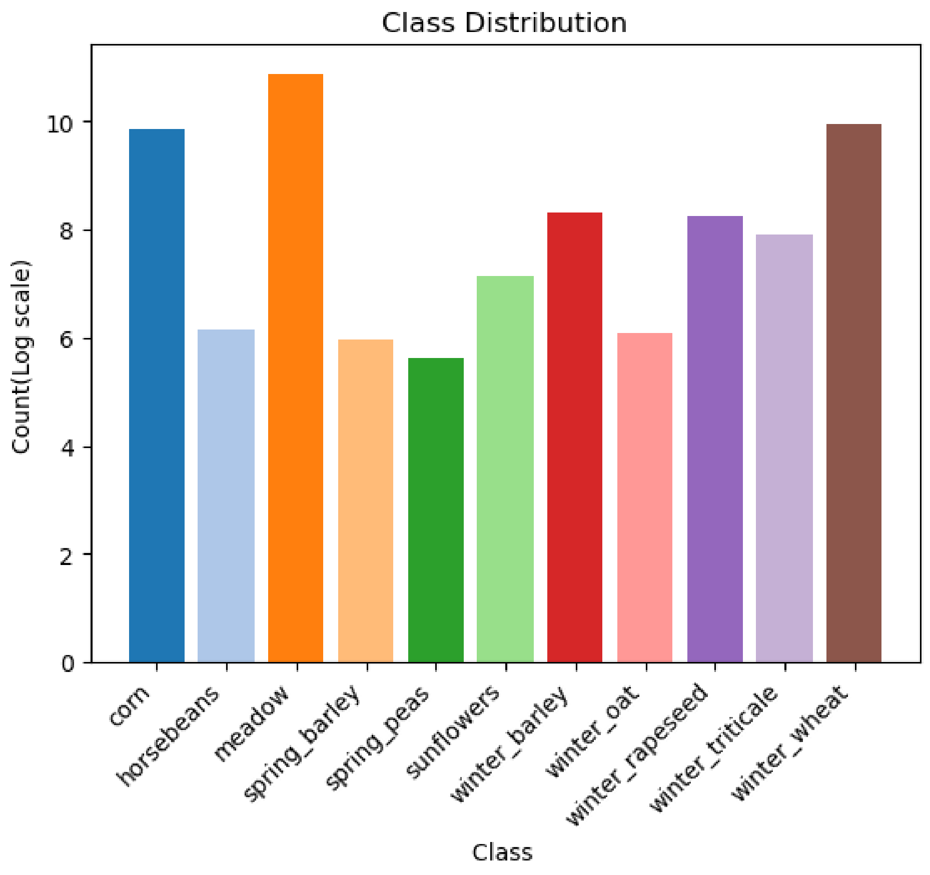
Experiments

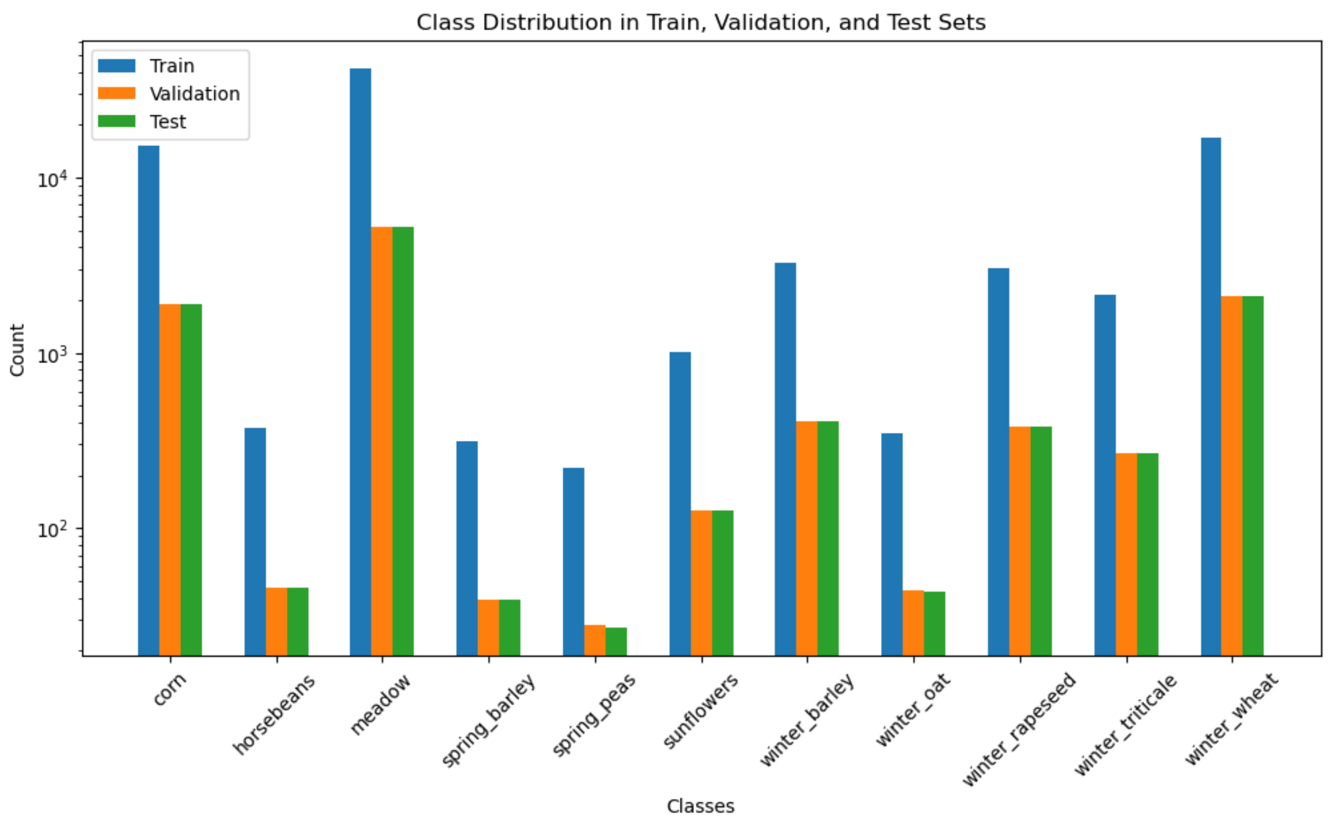
- Primary basline model – 1-nn
- Secondary baseline model – 1D-CNN
- Sampling inhomogeneity - linear interpolation

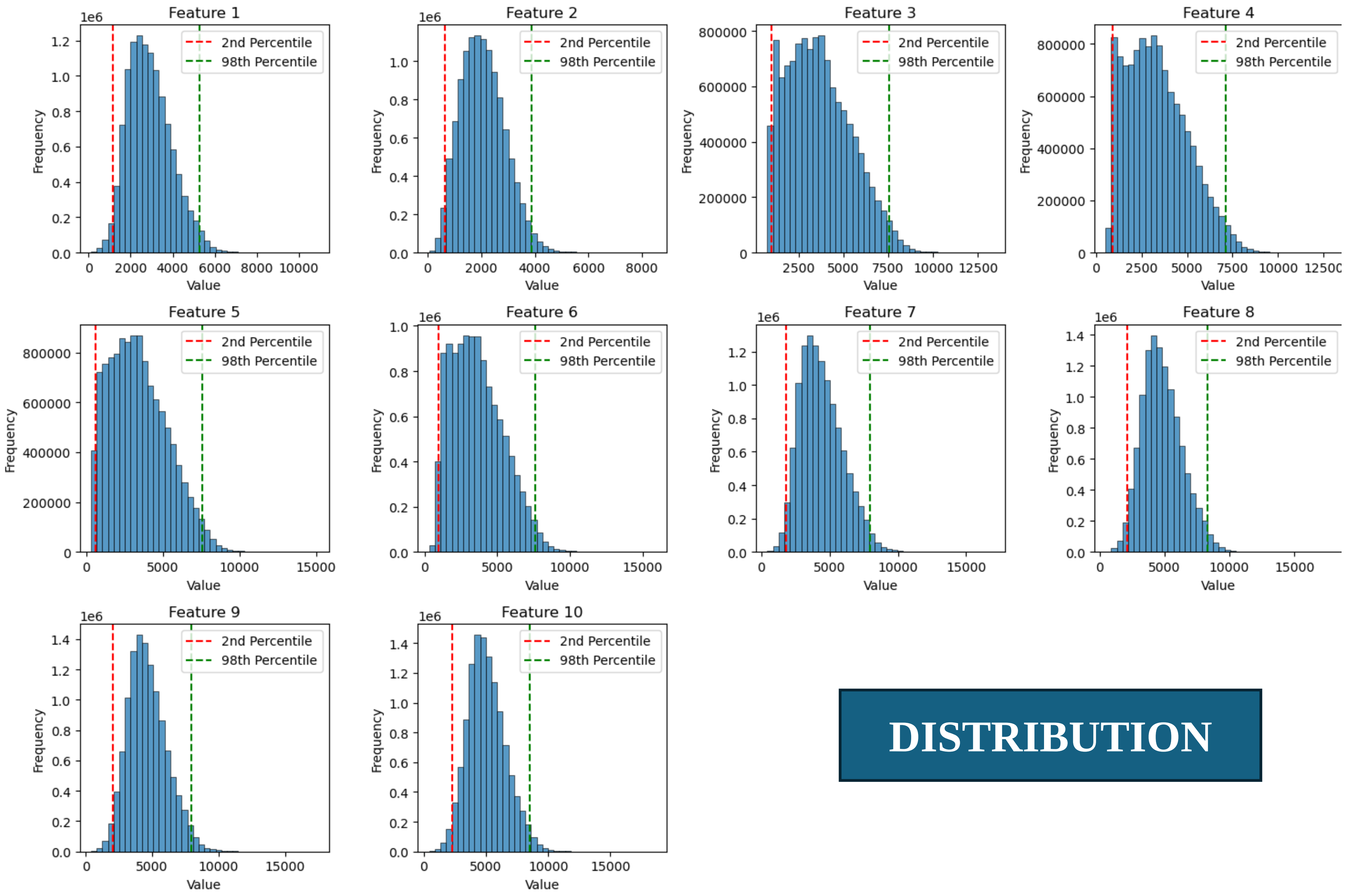
Table 2. Trainable Parameters and Time per Epoch

	Model			
Metric	**1D- CNN**	**LERN-Spec**	**LERN-Temp**	**LERN-Combo**
Trainable Parameters	41,323	1,412	15,391	31,965
Time per Epoch (secs)	9.21	12.6	17.78	32.3

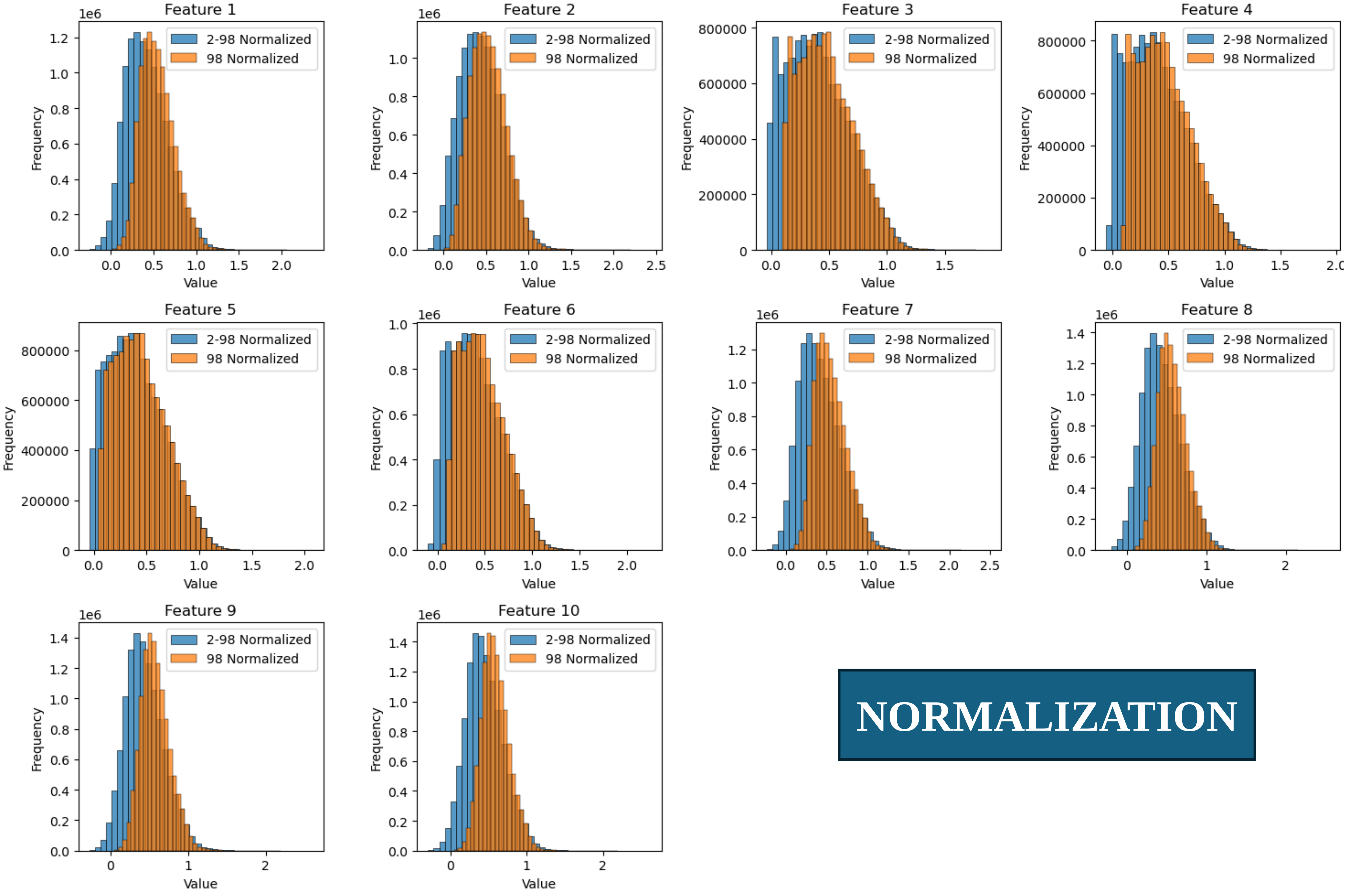
Class Distribution - Split







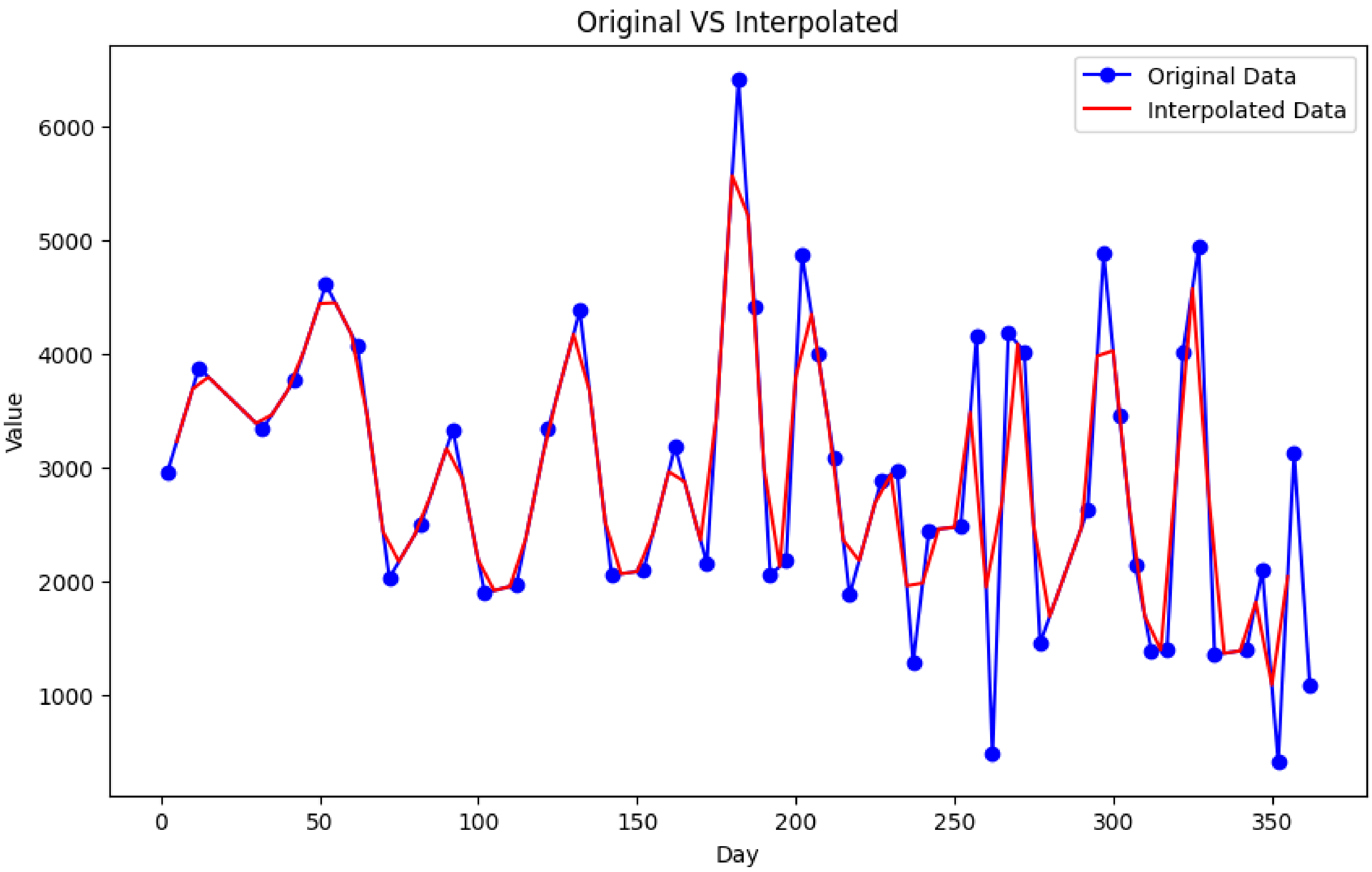
DISTRIBUTION



NORMALIZATION

Table 4. Outputs from combined datasets - BreizhCrops

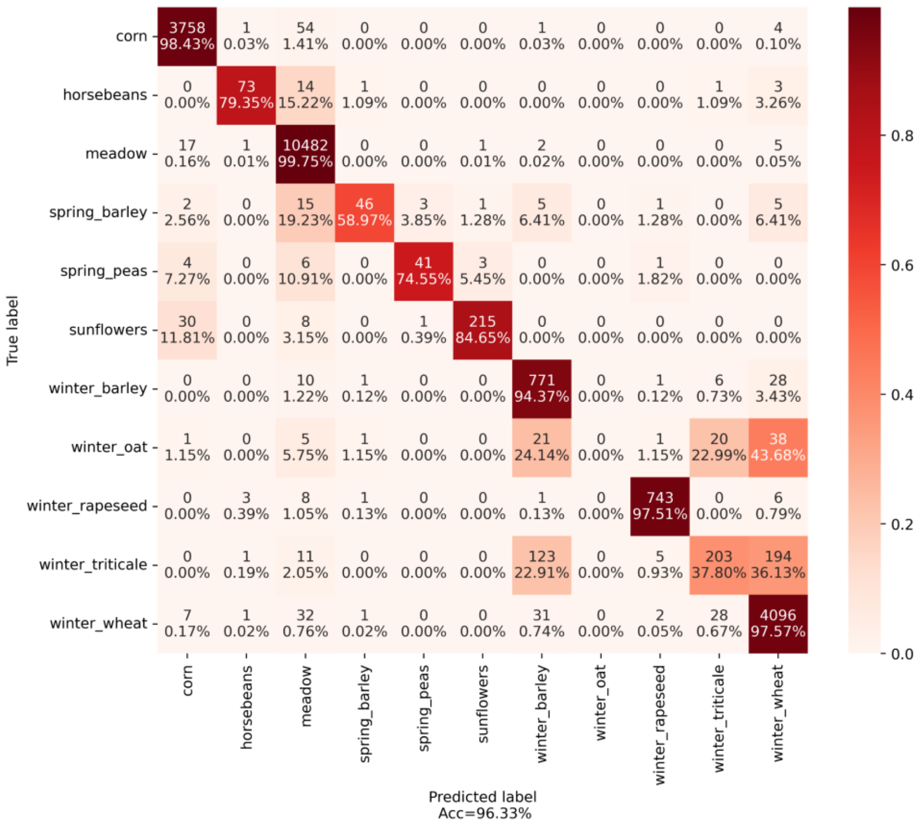
	Model		
Region	**LERN-Spec**	**LERN-Temp**	**LERN-Combo**
	Macro F1 Score		
frh01	0.68	-	-
frh02	0.70	-	-
frh03	0.65	-	-
frh04	0.70	0.77	**0.79**
	Weighted F1 Score		
frh01	0.76	-	-
frh02	0.77	-	-
frh03	0.74	-	-
frh04	0.78	**0.83**	**0.83**


Original VS Interpolated
Original Data
Interpolated Data
6000
5000
4000
3000
2000
1000
Value
0
50
100
150
200
250
300
350
Day

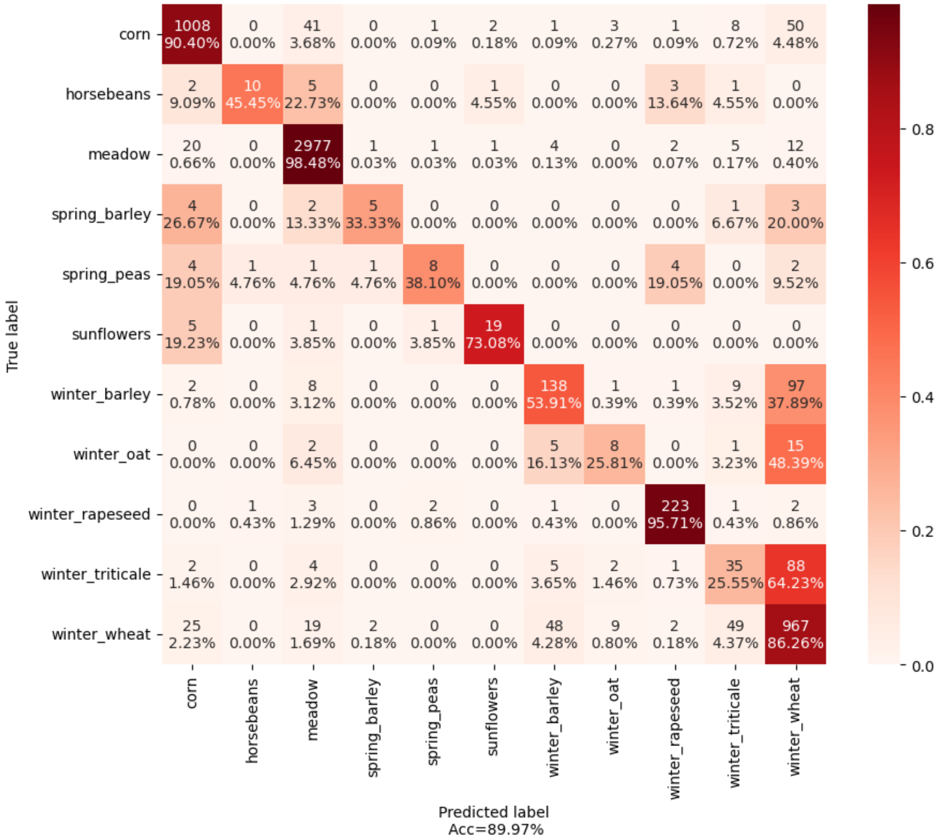
06

RESULTS

Baseline

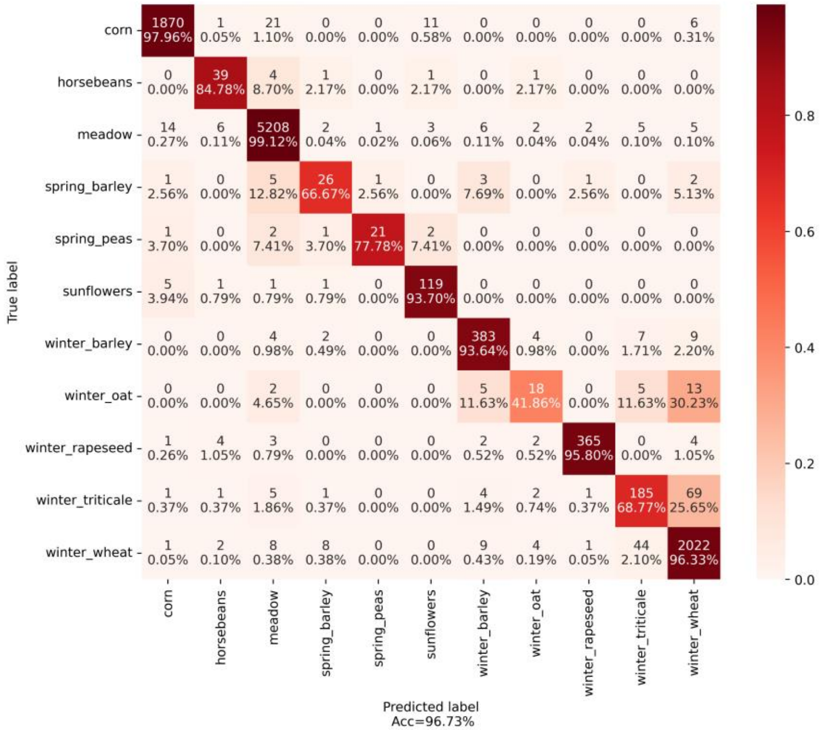


Output from CNN

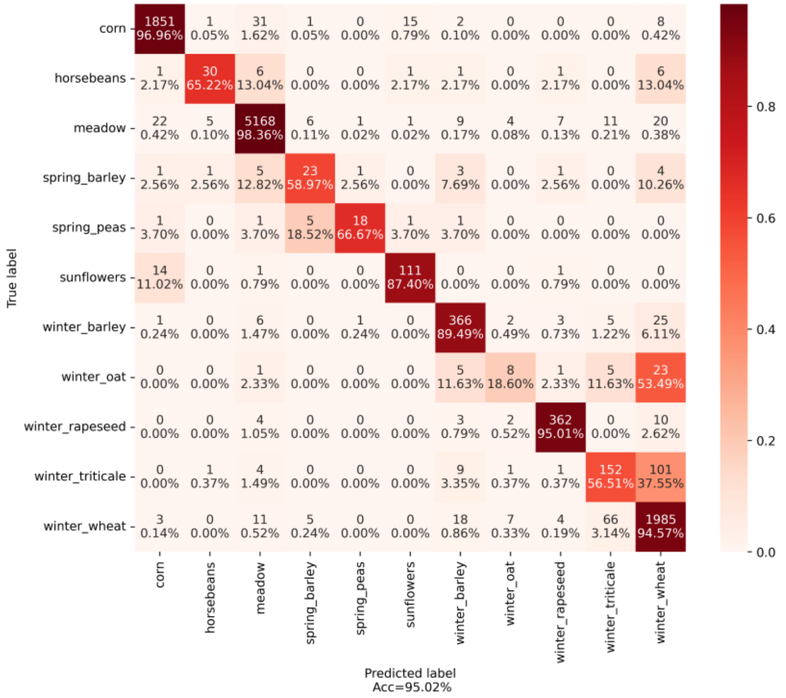


Output from 1-nn

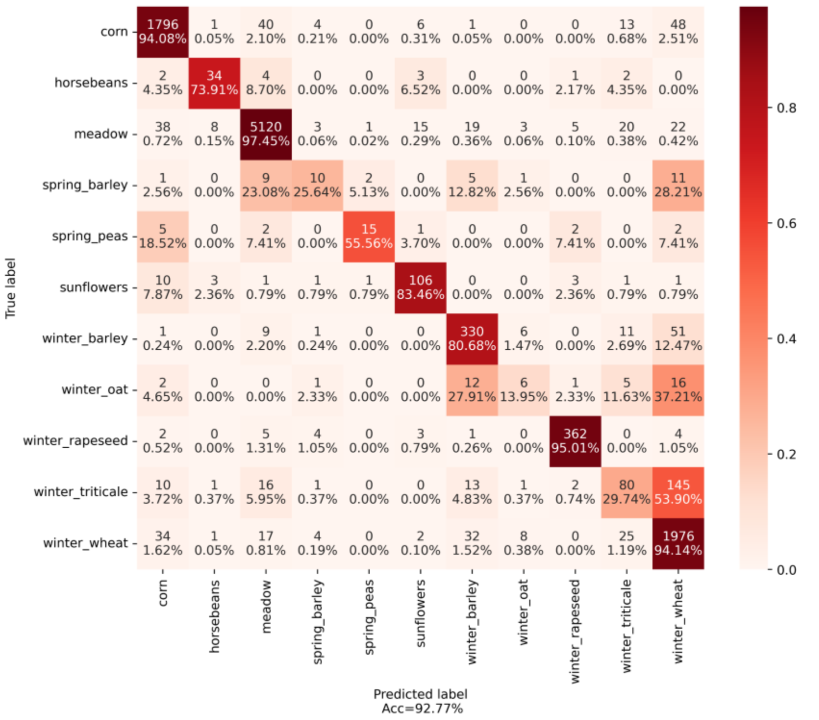
FR1-MiniTimeMatch



Combo output

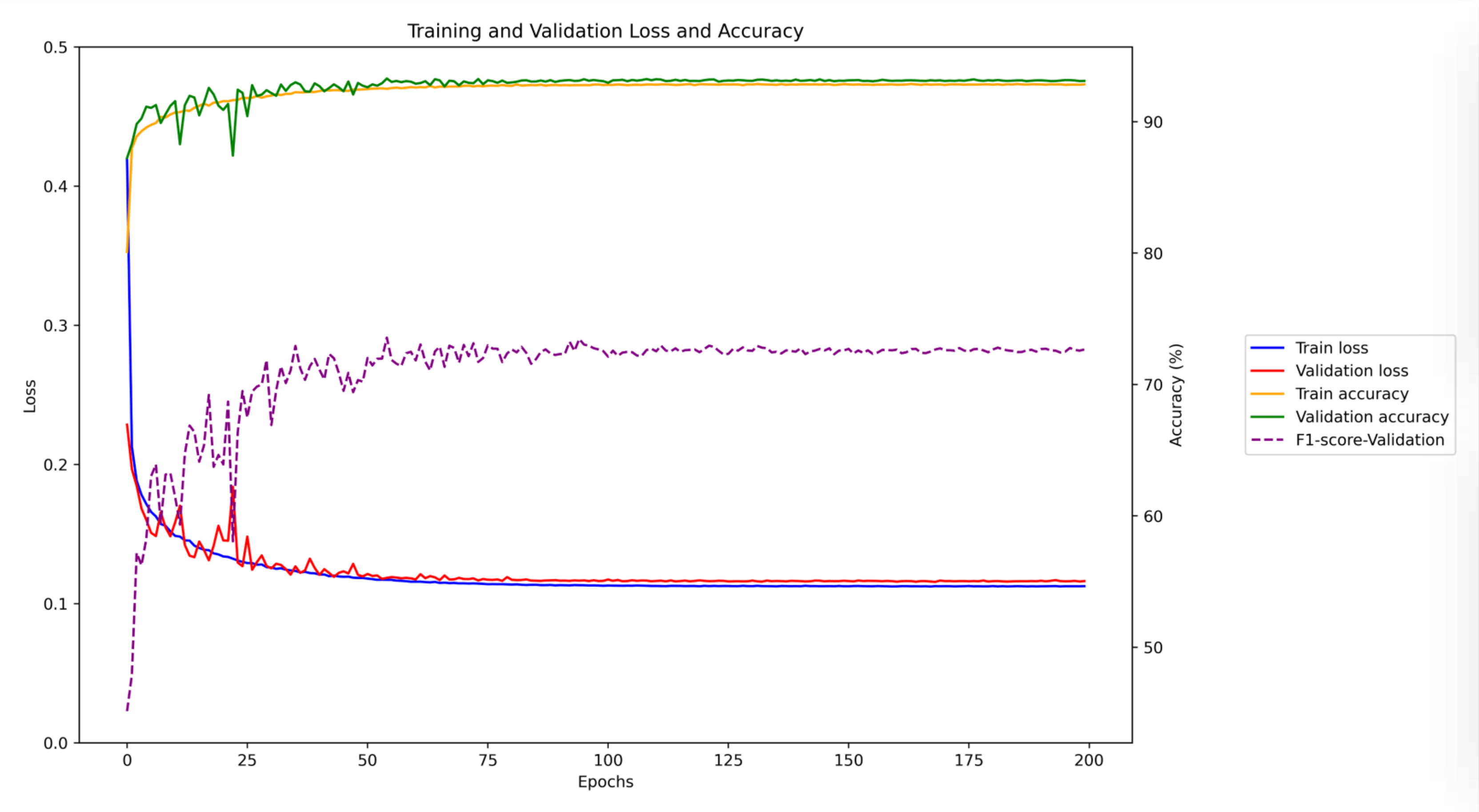


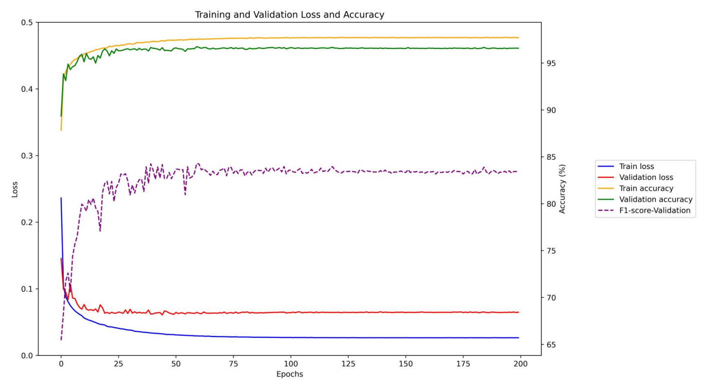
Temp output

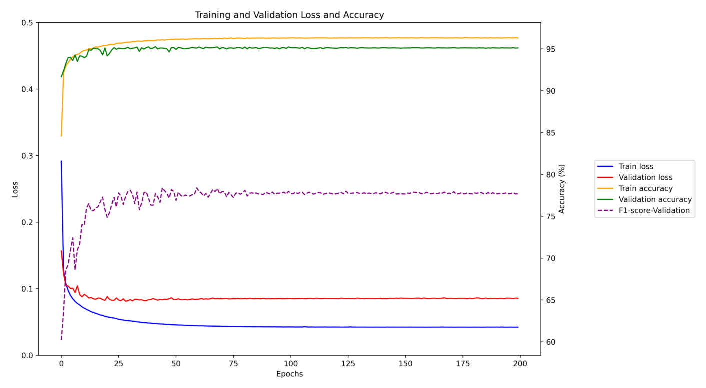


Spec output

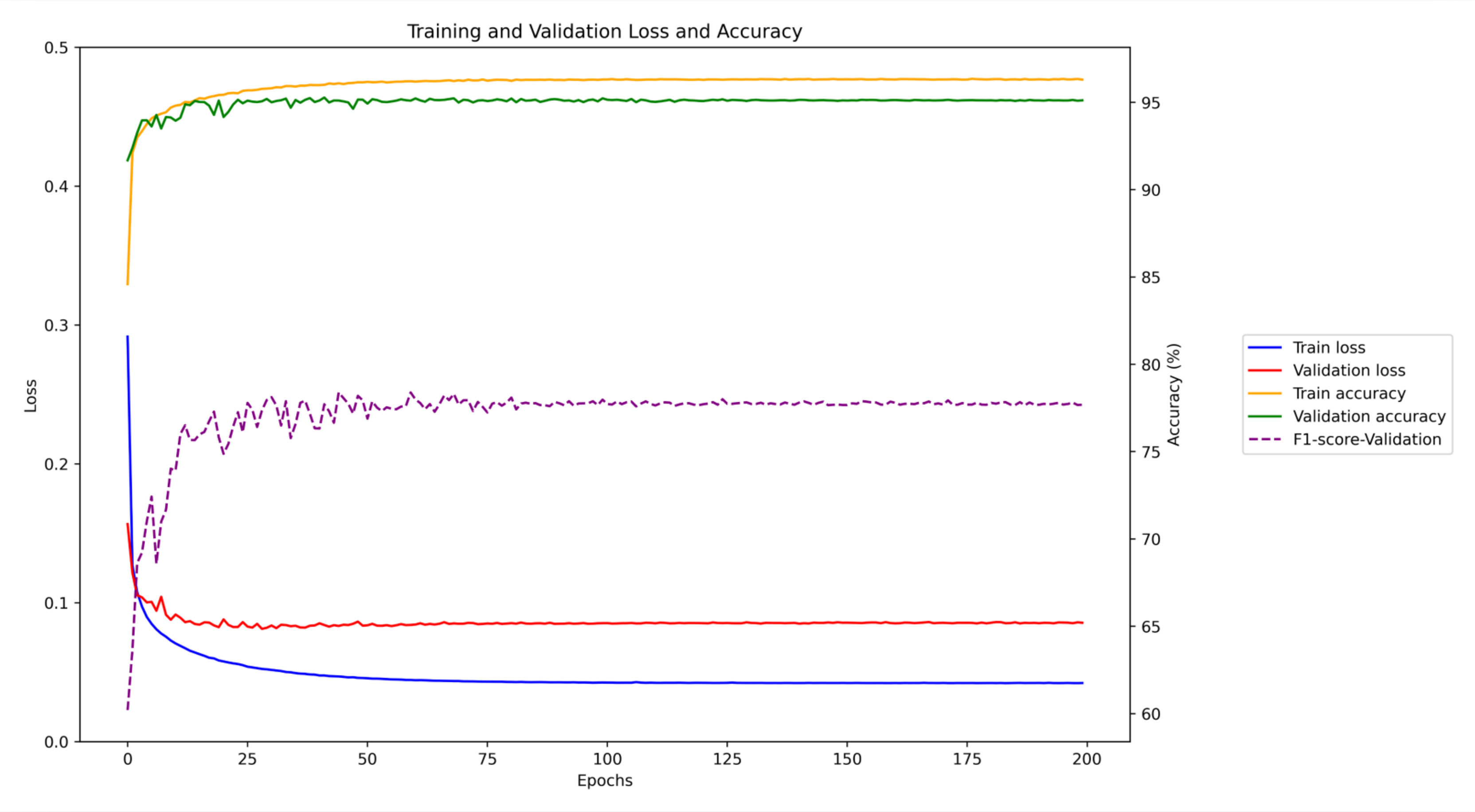
Curves for FR1



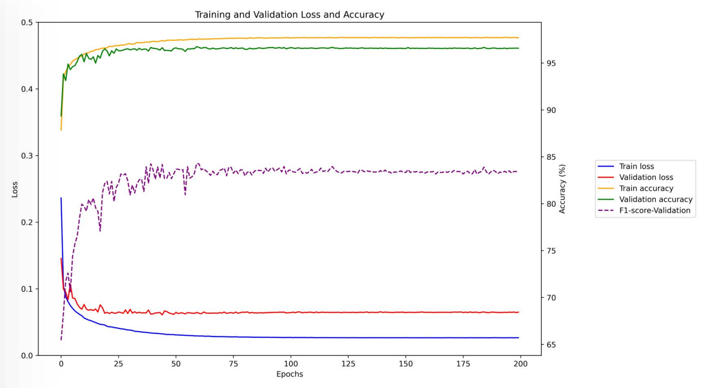




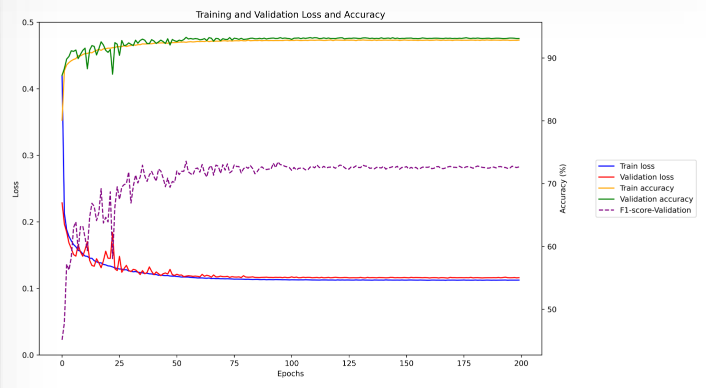
Cont…



Training and Validation Loss and Accuracy
Loss
Accuracy (%)
Epochs
Train loss
Validation loss
Train accuracy
Validation accuracy
F1-score-Validation

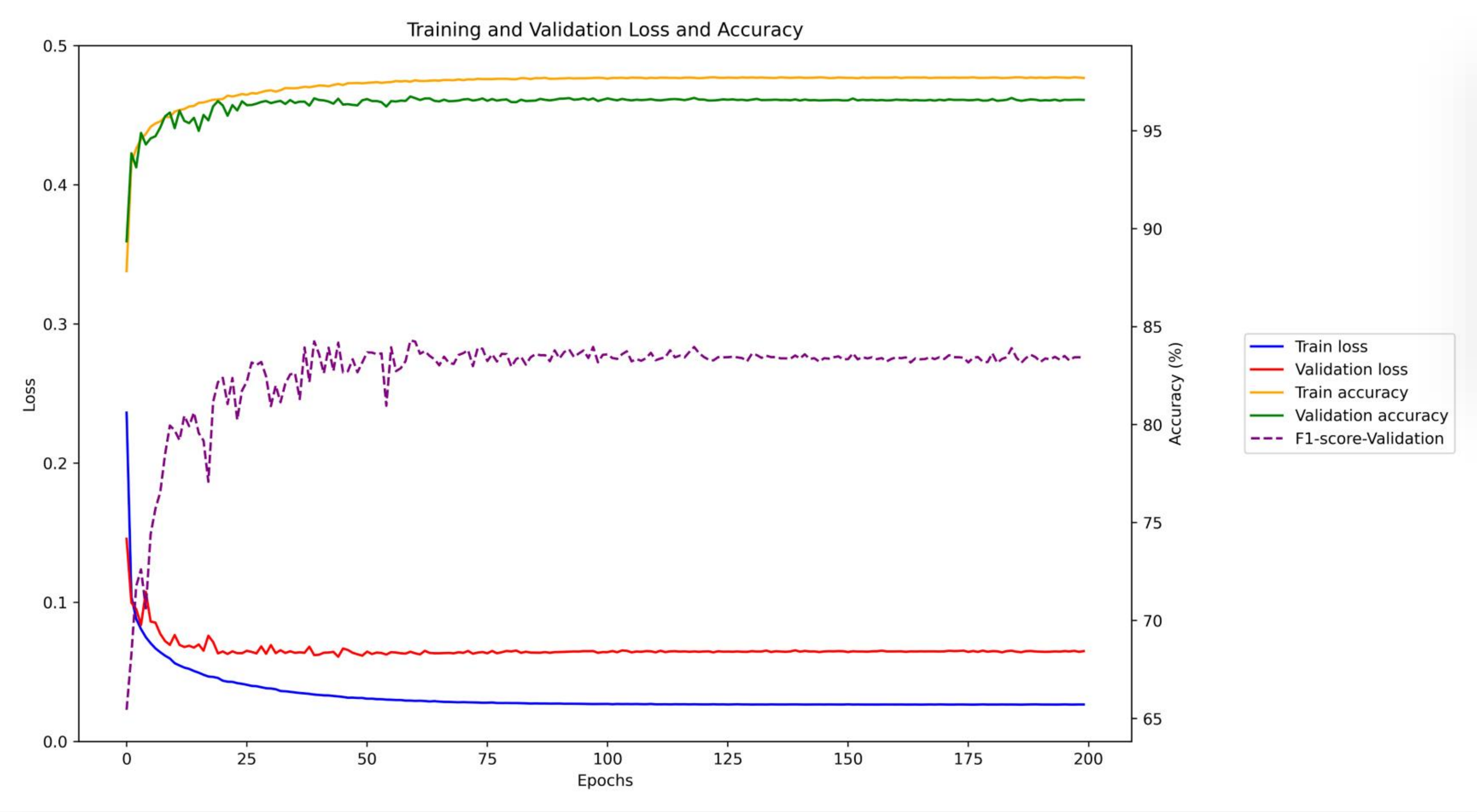


Training and Validation Loss and Accuracy



Training and Validation Loss and Accuracy

Cont…



Training and Validation Loss and Accuracy
Loss
Accuracy (%)
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Train loss
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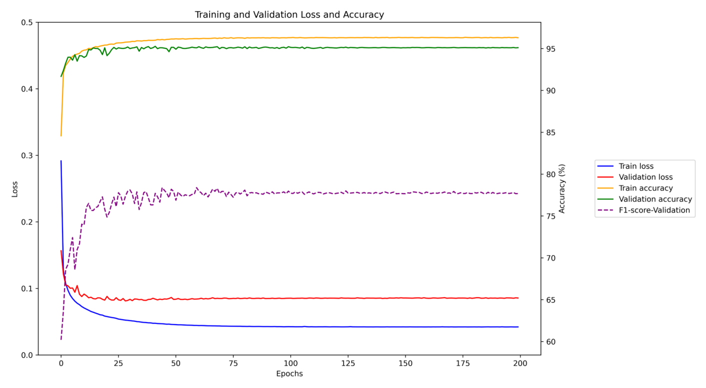
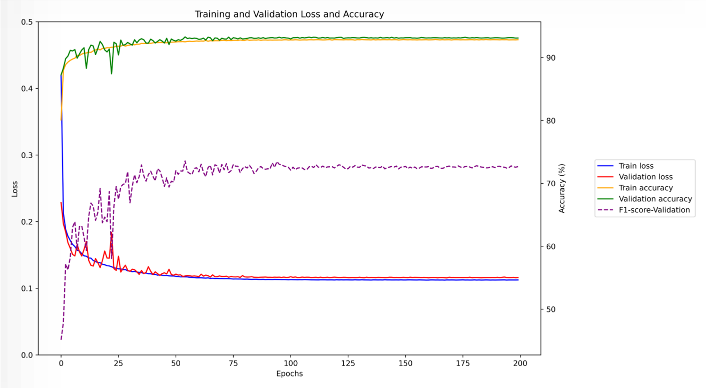
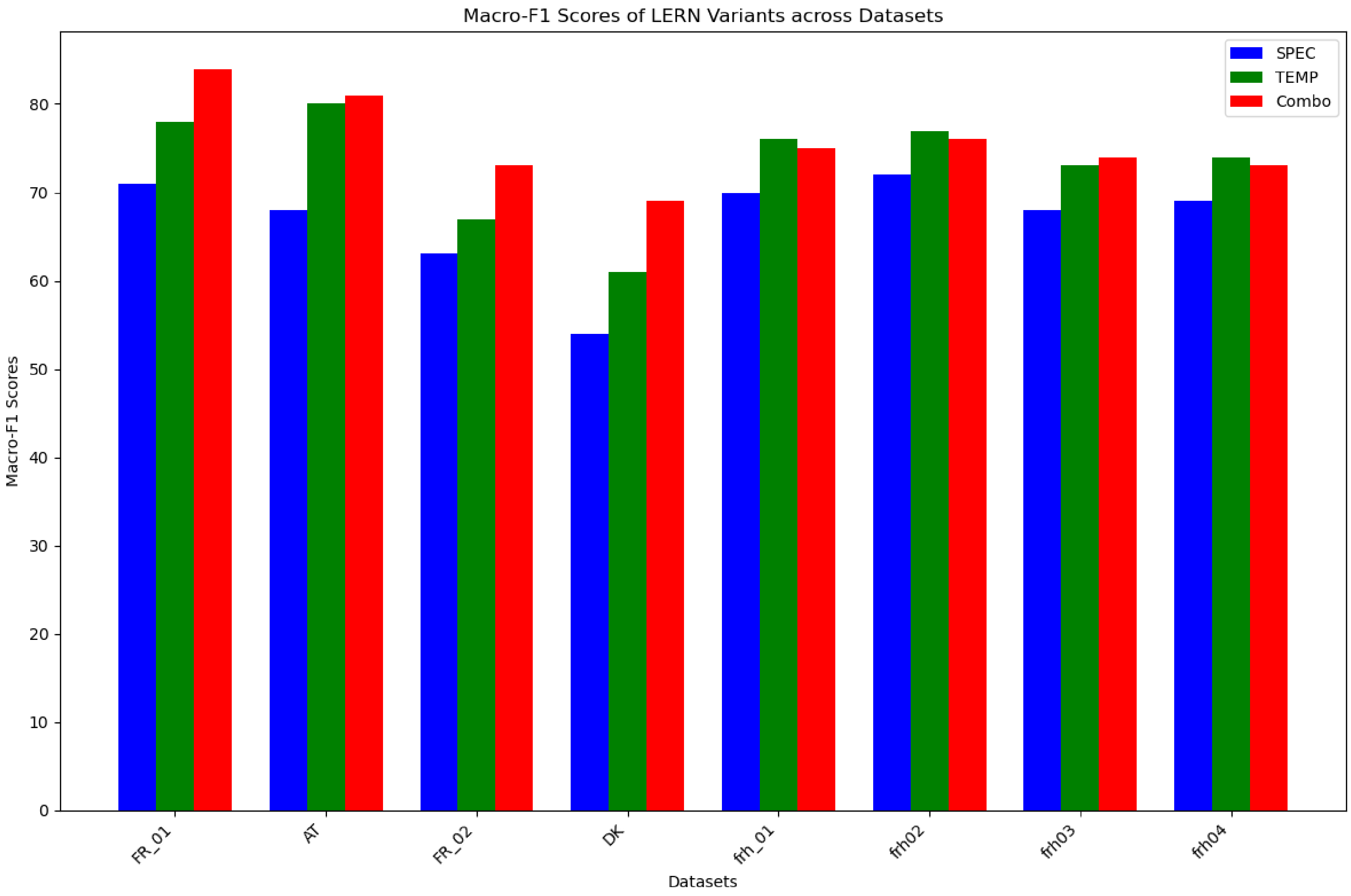
Validation accuracy
F1-score-Validation



Training and Validation Loss and Accuracy
Epochs



Training and Validation Loss and Accuracy
Epochs



Macro-F1 Scores of LERN Variants across Datasets
SPEC
TEMP
Combo
Macro-F1 Scores
0
10
20
30
40
50
60
70
80
FR_01
AT
FR_02
DK
frh_01
frh02
frh03
frh04
Datasets