Fault Detection and Diagnosis of Air Handling Units Based On Adversarial Multi-task Learning

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Content

- Background
- Challenge
- Architecture
- Methodolgy
- Experiment
- Results

Background

Research Purposes

Equipment aging

Misoperation

Network attacks

Prevent further damage

Avoid serious losses

Smart Building

A typical cyber-physical integration system(CPS)

Integrate various building control and functional modules

Typical CPS

Organic integration of each module

Research Status

FDD——Fault Detection and Diagnosis

Model-based methods

Signal-based methods

Data-driven methods

FDD

Data-driven Methods

LAB

Challenge

- Lack of Fault Contextualization
- Environmental Influence
- Seasonal Data Patterns

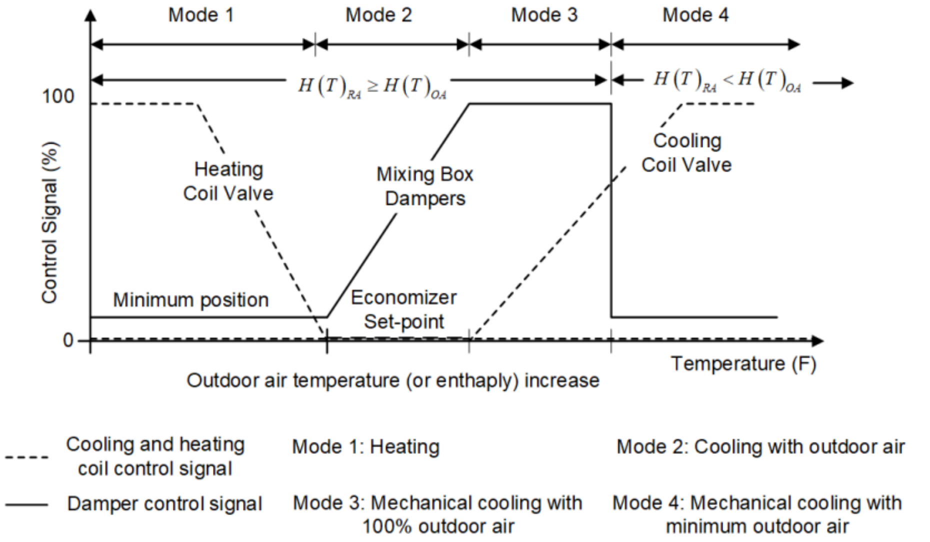


Fig. 2. Operating modes of AHU. An economizer set point refers to a predefined condition based on outdoor temperature, a combination of outdoor temperature and humidity, or outdoor enthalpy. When the outdoor temperature (and humidity) exceeds the economizer set point, the outdoor air intake will be limited to the minimum required to meet ventilation standards.

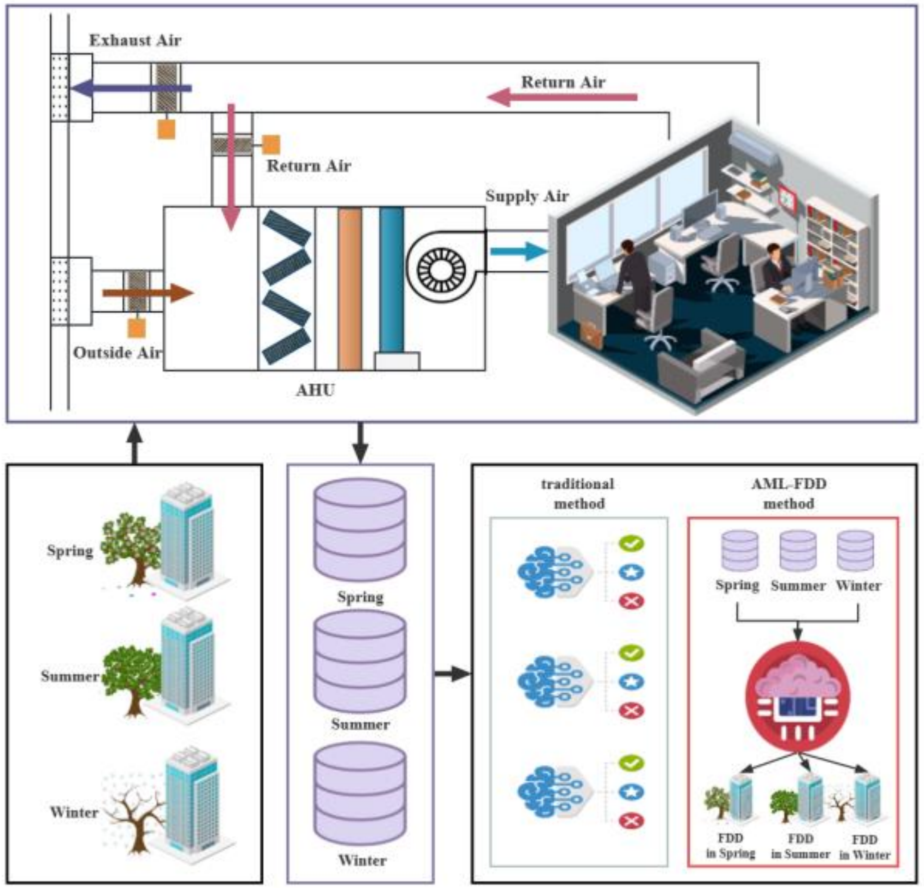


Fig. 1. An illustration of dealing with the building FDD in different ways: Single-task v.s. Multi-task.

Architecture

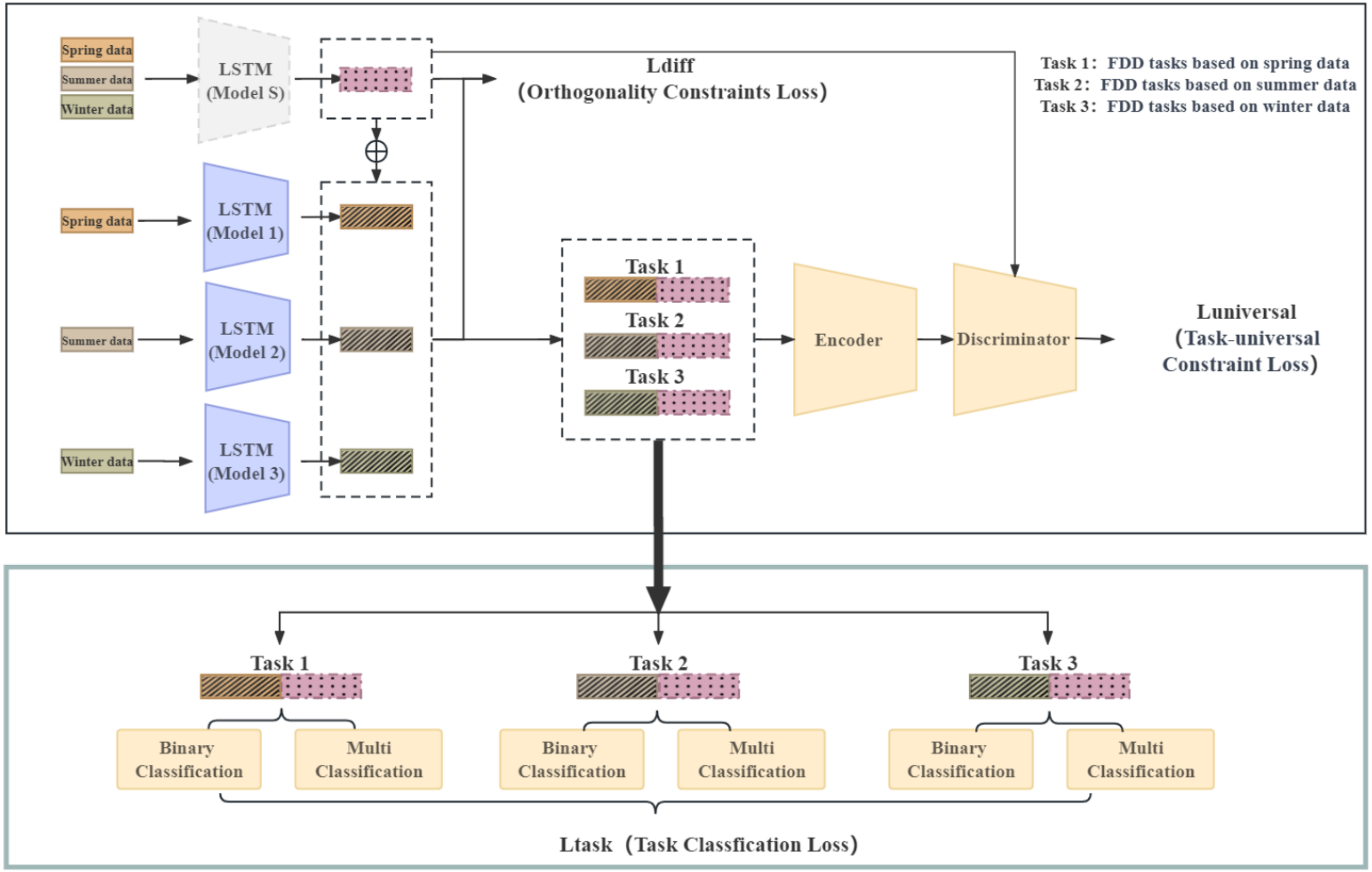
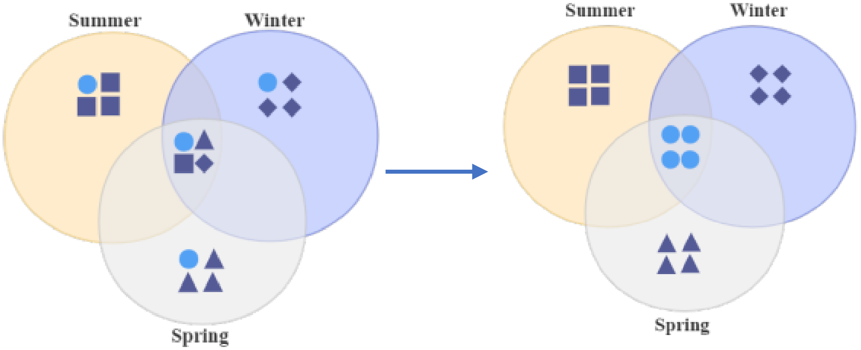


Fig. 3. Diagram of the proposed AML-FDD framework. At the Adversarial Multi-task Learning (AML) stage, adversarial training and orthogonality constraints are incorporated to learn the task-specific and task-shared features; the learned features are utilized for FDD classification tasks at the Fault Detection and Diagnosis (FDD) stage.

Methodology



Task Universal Constraints Loss

To separate the task-shared and task-specific features as clearly as possible.

$$L_{Universal} = \min_{\theta_s} \left(\lambda \max_{\theta_D} \left(\sum_{k=1}^{K} \sum_{i=1}^{N_k} d_i^k \log \left[D\left(E\left(\mathbf{x}^k \right) \right) \right] \right) \right) \tag{6}$$

Loss function

$$L = L_{\text{Task}} + \lambda L_{Universal} + \gamma L_{\text{Diff}}$$

STEP 01

STEP 02

STEP 03

STEP 04

Task Classification Loss

The networks are trained to minimize the cross-entropy between the predicted and true distributions for all tasks.

$$L_{\text{Task}} = \sum_{k=1}^{K} \alpha_k L\left(\hat{y}^{(k)}, y^{(k)} \right)$$

Orthogonality Constraints Loss

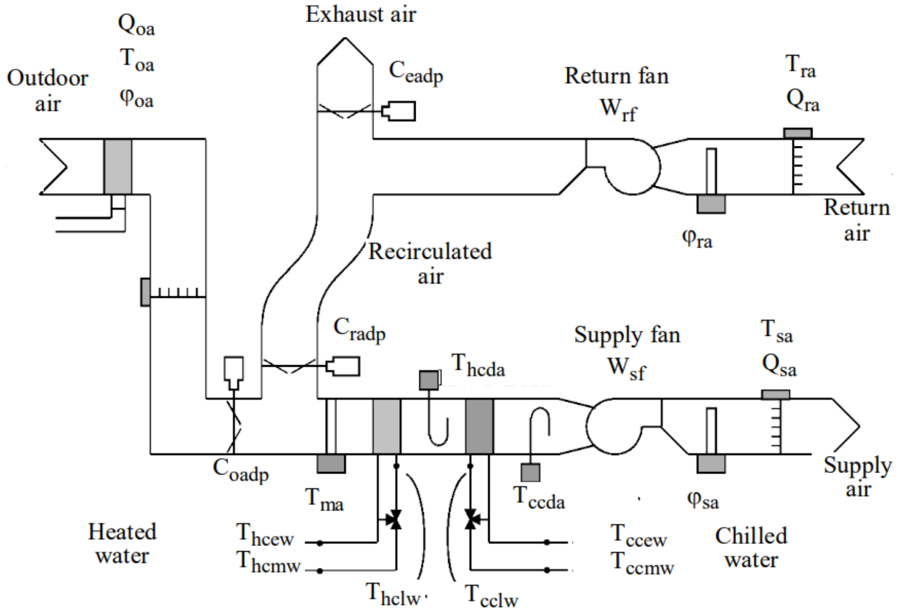
Inspired by other works, orthogonality constraints which penalize redundant potential representations and encourage task-shared and task-specific extractors to encode different aspects of the input are adopted.

$$L_{\text{diff}} = \sum_{k=1}^{K} \left\| \mathbf{S}^{k\top} \mathbf{H}^k \right\|_F^2$$

Experiment

System

- An Air Handling Unit (AHU) connects the heating and cooling units to the building area, controls the ventilation intake of the building, and significantly affects the energy consumption of heating, cooling, and ventilation and the temperature and humidity of the supply air. Due to the high intensity of operations, AHU is prone to degradation.



Datasets

- We evaluated the proposed AML-FDD framework using two datasets from the ERS test facility.
- the ASHRAE research project 1312 (RP-1312)
- the ASHRAE research project 1020 (RP-1020)

Experiment

Fault Types

- Four main categories of experimental faults
- RP-1312—17 fault types
- RP-1020—8 fault types

Experimental Set-up

- Faults were introduced to the ERS testbed in RP-1312 and RP-1020 under three different seasonal conditions.
- the FDD task was conducted as a binary and multi-class classification task, respectively.

TABLE I
NUMBER OF FAULT CATEGORIES AND CORRESPONDING DATA SIZES FOR EACH TASK (RP-1312)

Categories	Second Categories	Fault Type Label	Summer(Task1)[1]	Spring(Task2)[2]	Winter(Task3)[3]
Fault-Free	-	0	2160	3600	2160
Controlled Device	OA Damper Stuck	1	720	1440	720
	OA Damper Leak	2	1440	-	1440
	EA Damper Stu	3	1440	2160	1440
	Cooling Coil Valve Stuck	4	2880	2160	1440
	Heating Coil Valve Leaking	5	2160	-	-
Equipment	AHU Duct Leaking	6	1440	-	-
	Heating Coil Fouling	7	-	-	1440
	Heating Coil Reduced Capacity	8	-	-	2160
	Return Fan complete failure	9	-	720	-
	Air filter blockage fault	10	720	1440	-
Controller	Return Fan at fixed speed	11	720	-	-
	Cooling Coil Valve Control unstable	12	720	-	-
	Cooling Coil Valve Reverse Action	13	-	720	-
	Mixed air damper unstable	14	-	720	-
	Mixed air damper unstable /Cooling Coil Control	15	-	720	-
	Sequence of Heating and cooling unstable	16	-	1440	-
Sensor	OA temperature sensor bias	17	-	1440	-

[1,2,3] Taking into account the Fault Free condition, there are 10, 11, and 7 fault categories in Summer (Task 1), Spring (Task 2), and Winter (Task 3), respectively, of RP-1312.

TABLE II
NUMBER OF FAULT CATEGORIES AND CORRESPONDING DATA SIZES FOR EACH TASK (RP-1020)

Categories	Fault Type Label	Summer(Task1)[4]	Spring(Task2)[5]	Winter(Task3)[6]
Fault-Free	0	5884	1488	2475
Static Pressure Sensor Fault	1	405	1289	2467
Leaking Cooling Coil Valve	2	-	4379	1274
Unstable Static Pressure Control	3	1367	3751	2066
Fouling Cooling Coil	4	-	4305	-
Leaking Re-circulation Damper	5	-	4435	-
Slipping Fan Belt	6	2597	-	4365
Coil "Capacity" Fault	7	2896	-	-
Stuck Re-circulation Damper	8	2210	-	4648

[4,5,6] Considering the Fault Free condition, there are 6 fault categories in all three tasks of RP-1020.

Experiment

Baselines

- MT-CNN: A model of convolutional neural networks where only the lookup layer is shared and the other layers are task-specific private.
- MT-DNN: Contains bag-of-words inputs and multilayer perceptrons with shared hidden layers.
- FS-MTL:This model ignores that some features are task-dependent and cannot be shared.
- SP-MTL: each task is assigned a private LSTM layer and a shared LSTM layer.

Model Parameters

- A random selection of 10% of the data for the test set
- The remaining 70% of the datasets were employed for training purposes
- The remaining 20% were allocated for validation
- We choose a learning rate of 0.01, lambda is 0.05, and gamma is 0.01.

Results

FDD via Binary Classification

- The performance for the three tasks of RP-1312 is different.
- From the two table, it can be seen that multi-task models generally outperformed single-task models. Specifically, the accuracy value by AML-FDD improved by an average of 4.0% and 9.9% compared to the single task.
- RP-1020 were generally slightly higher than in RP-1312.
- the accuracy values of the three tasks in RP-1312 were relatively consistent.

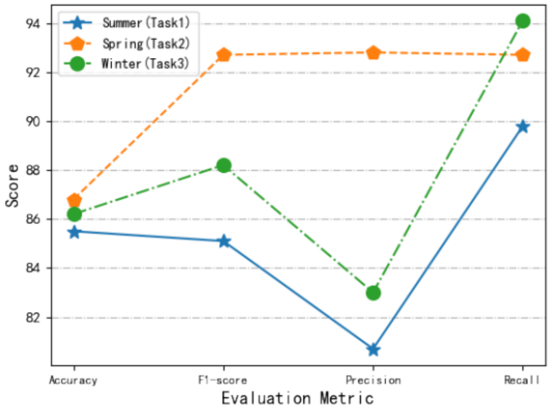


Fig. 5. Evaluation metrics of binary classification via AML-FDD for RP-1312

TABLE III
FDD PERFORMANCE VIA BINARY CLASSIFICATION FOR RP-1312

Task	Single Task Model			Multi-task Model				
	LSTM	BiLSTM	sLSTM	MT-DNN	MT-CNN	FS-MTL	SP-MTL	AML-FDD
Summer(Task1)	79.5	80.5	82	82.2	83.5	84.5	85.2	**85.5±0.1**
Spring(Task2)	85.2	86	80.5	84.2	84.5	86.2	84.7	**86.2±0.2**
Winter(Task3)	81.5	81.7	82.5	85.7	85.5	83.7	86.5	**86.8±0.2**
average	82.1	82.8	81.7	84.1	84.5	84.8	85.5	**86.2±0.1**

TABLE IV
FDD PERFORMANCE VIA BINARY CLASSIFICATION FOR RP-1020

Task	Single Task Model			Multi-task Model				
	LSTM	BiLSTM	sLSTM	MT-DNN	MT-CNN	FS-MTL	SP-MTL	AML-FDD
Summer(Task1)	78.5	81.3	71.2	77.8	75.4	82.3	84.5	**91.8±0.3**
Spring(Task2)	80	80.9	71.5	72.8	71.6	78.1	76.9	**82.6±0.1**
Winter(Task3)	80.5	79.3	72.5	77.5	78.8	85.7	80.6	**87.1±0.3**
average	79.7	80.5	71.7	76	75.3	82	80.7	**87.2±0.3**

Results

FDD via Multi-class Classification

- **Comparison of Classification Models:** The RP-1312 exhibits lower accuracy compared to the binary classification model due to the increased complexity in reducing redundancy between task-shared and task-specific features in multi-class tasks.
- **Superiority of adversarial networks and orthogonality constraints:** Both SP-MTL and AML-FDD demonstrate higher accuracy over other multi-task models like MT-DNN, MT-CNN, and FS-MTL, indicating that separating task-shared and task-specific features is beneficial. Additionally, AML-FDD surpasses SP-MTL by 2.6% in accuracy.

TABLE V
FDD PERFORMANCE VIA MULTI-CLASS CLASSIFICATION FOR RP-1312

Task	Single Task Model			Multi-task Model				
	LSTM	BiLSTM	sLSTM	MT-DNN	MT-CNN	FS-MTL	SP-MTL	AML-FDD
Summer(Task1)	70.2	66.3	69.2	75.5	74.5	74.7	76	**77.6±0.5**
Spring(Task2)	78.8	66.8	79.1	81.7	81.5	82.5	83	**84.7±0.2**
Winter(Task3)	68.8	67.1	77.4	80.7	83.2	83.2	81.2	**85.8±0.3**
average	72.6	66.7	75.2	79.3	79.8	79.8	80.1	**82.7±0.3**

TABLE VI
FDD PERFORMANCE VIA MULTI-CLASS CLASSIFICATION FOR RP-1020

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	LSTM	BiLSTM	sLSTM	MT-DNN	MT-CNN	FS-MTL	SP-MTL	AML-FDD
Summer(Task1)	68.9	71.3	65.7	73.4	71.1	75.1	77.7	**83.4±0.2**
Spring(Task2)	62.4	66	64	73.6	72.9	83.7	80.8	**88.1±0.1**
Winter(Task3)	66.8	70.7	69.3	72.1	74.8	83.9	81.4	**91.6±0.4**
average	66	73.7	66.3	73	72.9	80.9	80	**87.7±0.2**

Results

FDD via Multi-class Classification

- **Seasonal Variation in Fault Detection:** Winter shows the highest accuracy due to a more even distribution of samples and fewer fault types.In contrast, Summer has a more uneven distribution, and Spring benefits from a larger sample size, which may provide more information for the model, leading to better performance.
- **Winter Season Analysis:** Winter has fewer fault types and more normal samples, which leads to higher accuracy in binary classification due to more balanced labels. However, the multi-class classification accuracy is lower due to the imbalance in label distribution across fault types.

TABLE V
FDD PERFORMANCE VIA MULTI-CLASS CLASSIFICATION FOR RP-1312

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average	72.6	66.7	75.2	79.3	79.8	79.8	<u>80.1</u>	**82.7±0.3**

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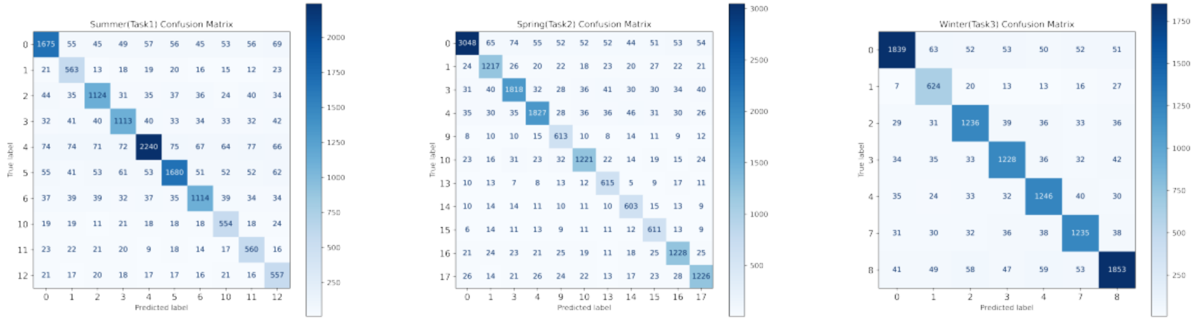
Winter(Task3)	66.8	70.7	69.3	72.1	74.8	<u>83.9</u>	81.4	**91.6±0.4**
average	66	73.7	66.3	73	72.9	<u>80.9</u>	80	**87.7±0.2**

Results

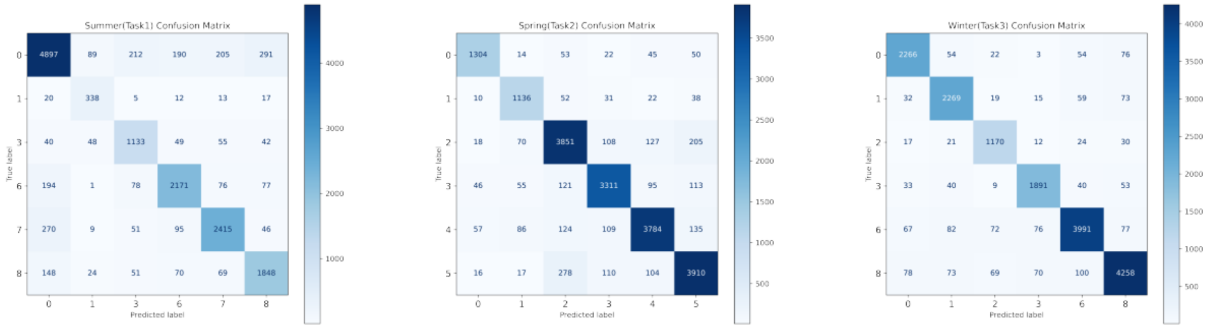
FDD via Multi-class Classification

- **<u>Data Imbalance in Summer</u>**: Summer (Task 1) of RP-1020 shows a pronounced issue of data imbalance with a surplus of fault-free samples (label "0"), causing misclassification of other labels as "0".
- **<u>Binary Classification Accuracy in Summer</u>**: The data imbalance contributes to higher binary classification accuracy for Summer (Task 1) due to the predominance of fault-free samples.



(a) Summer (Task1) of RP-1312 (b) Spring (Task2) of RP-1312 (c) Winter (Task3) of RP-1312

Fig. 6. Confusion Matrices of multi-class classification results by AML-FDD for RP-1312 in the Summer, Spring, and Winter.



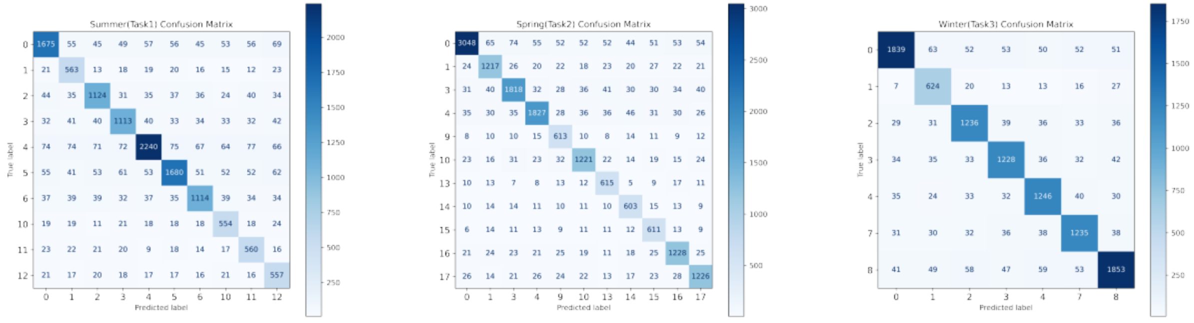
(a) Summer (Task1) of RP-1020 (b) Spring (Task2) of RP-1020 (c) Winter (Task3) of RP-1020

Fig. 7. Confusion Matrices of multi-class classification results by AML-FDD for RP-1020 in the Summer, Spring, and Winter.

Results

FDD via Multi-class Classification

- **<u>Spring vs. Winter Performance</u>**: The presence of two task-specific fault types in Spring (Task 2) accounts for the lower multi-class classification performance compared to Winter (Task 3). However, Spring performs better than Summer due to having more data for these task-specific faults.
- **<u>Uniform Data Distribution in Winter</u>**: Winter exhibits a more uniform data distribution, and the overlap of fault types across seasons reduces the number of task-specific features, resulting in higher quality learned features and thus higher multi-classification accuracy.



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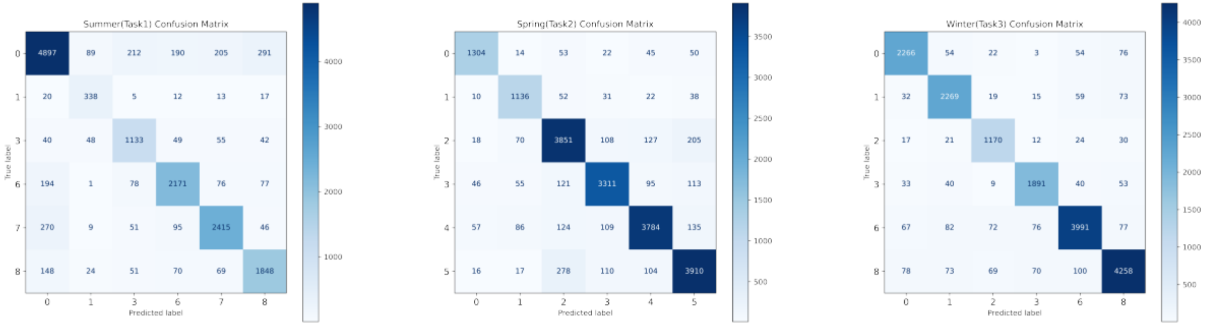

(a) Summer (Task1) of RP-1020 (b) Spring (Task2) of RP-1020 (c) Winter (Task3) of RP-1020

Fig. 7. Confusion Matrices of multi-class classification results by AML-FDD for RP-1020 in the Summer, Spring, and Winter.

Thank You！