Supplementary Material B: RML Algorithm Details

DETAILED WORKFLOW AND EQUATIONS FOR RML

The Related Incident Adaptation Model-Agnostic Meta-Learning (RML) algorithm is utilized to derive an optimal, generalizable initial model parameter θ by training on diverse stall precursor-related tasks. The process involves alternating between Inner Loop updates (task-specific adaptation) and Outer Loop updates (meta-optimization).

Inner Loop Update

In the inner loop, for each sampled task $\mathcal{T}_i$, the model is updated on the support set using one or more steps of gradient descent to find the task-specific parameters θ'_i:

$$\theta'_i = \theta - \alpha_{IL} \nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta), \tag{S1}$$

where α_{IL} is the inner loop learning rate, $\mathcal{L}$ is the loss function, and θ'_i is the updated parameter set for task $\mathcal{T}_i$.

Outer Loop Update

The adapted parameters θ'_i are then evaluated on the query set of $\mathcal{T}_i$. The gradients from all tasks are accumulated to update the model's initial parameters θ (the meta-optimization step), enhancing the model's overall generalization ability:

$$\theta \leftarrow \theta - \beta_{OL} \nabla_\theta \sum_{\mathcal{T}_i \sim (\mathcal{T}_{train})} \mathcal{L}_{\mathcal{T}_i}(f_{\theta'_i}). \tag{S2}$$

Here, β_{OL} is the outer loop learning rate. This alternating process continues until convergence, yielding the optimal initial hyperparameters θ_m.

Fine-tuning Phase

In the subsequent fine-tune phase, the optimal initial hyperparameters θ_m are loaded. All data in the limited fine-tune set $\mathcal{D}_{fine}$ is treated as a single task. The data is split into a support set S and a query set Q. The model is updated multiple times on the support set S and evaluated on Q, resulting in the final specialized model parameters θ_s, which are tailored for the specific aircraft stall identification task.