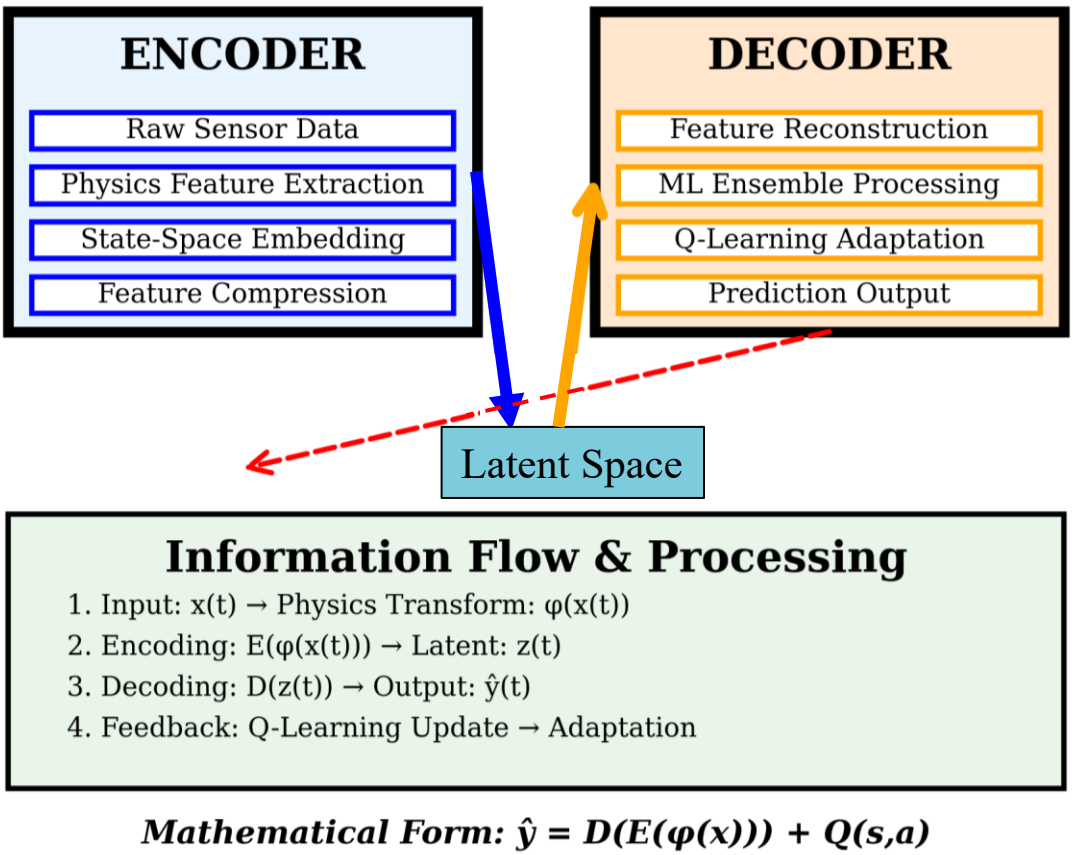
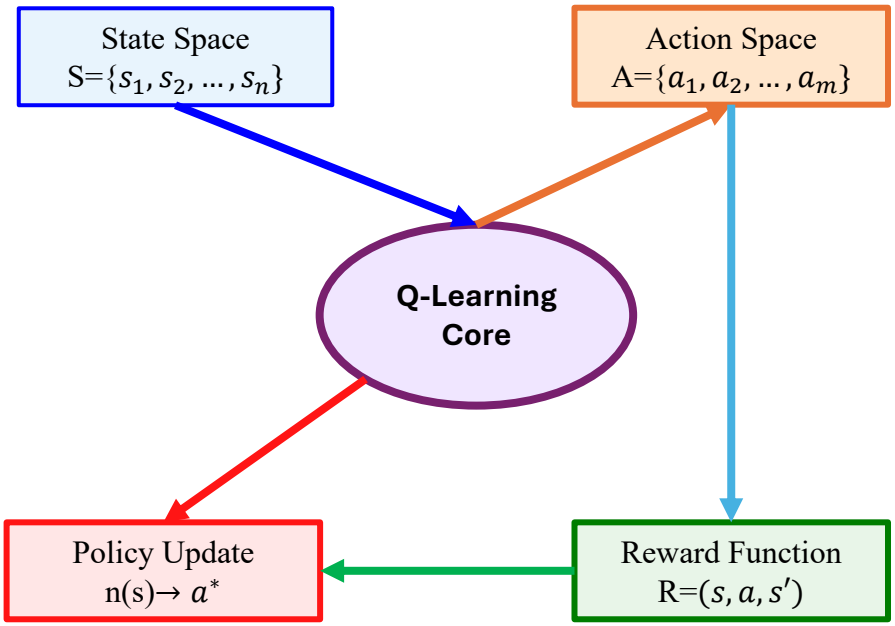


Figure: Physics Informed Self Adaptive Hybrid Machine Learning(PISAHML) Encode-Decode System



$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \max Q(s',a') - Q(s,a)]$$

α: *Learning Rate*, γ: *Discount Factor*, ε: *Exploration Rate*

Figure: Self Adaptive Q-Learning Mechanism

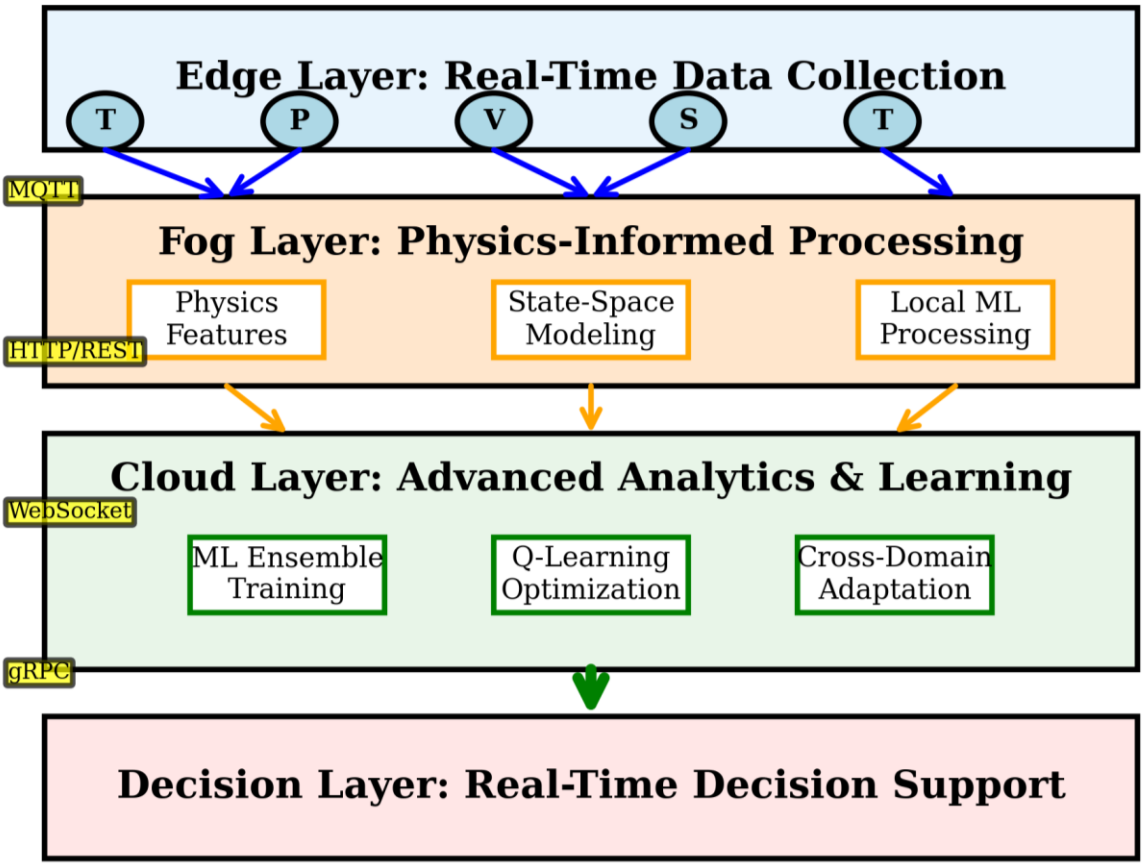


Figure: PISAHML Networking Architecture

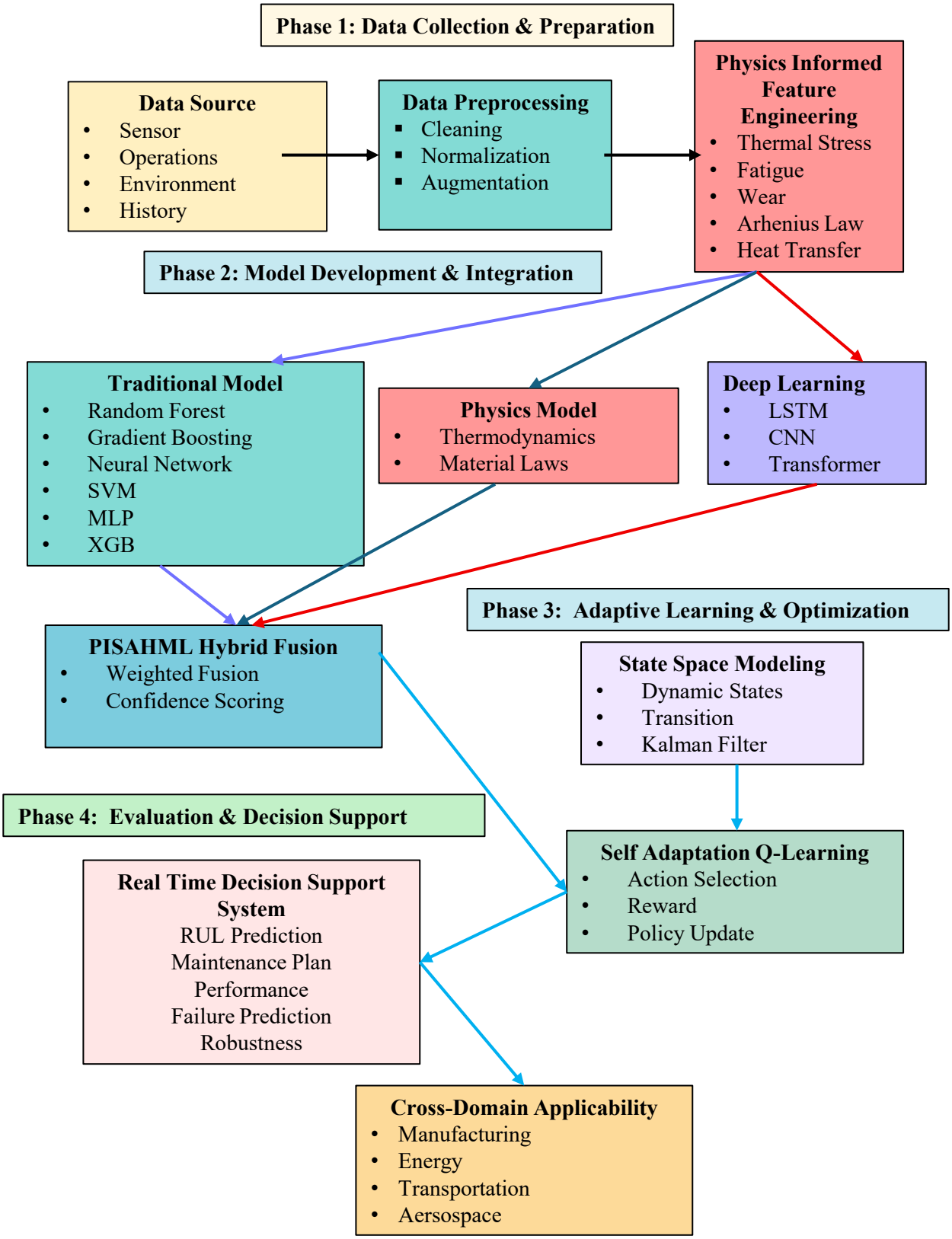


Figure: Full Working Flow Summary

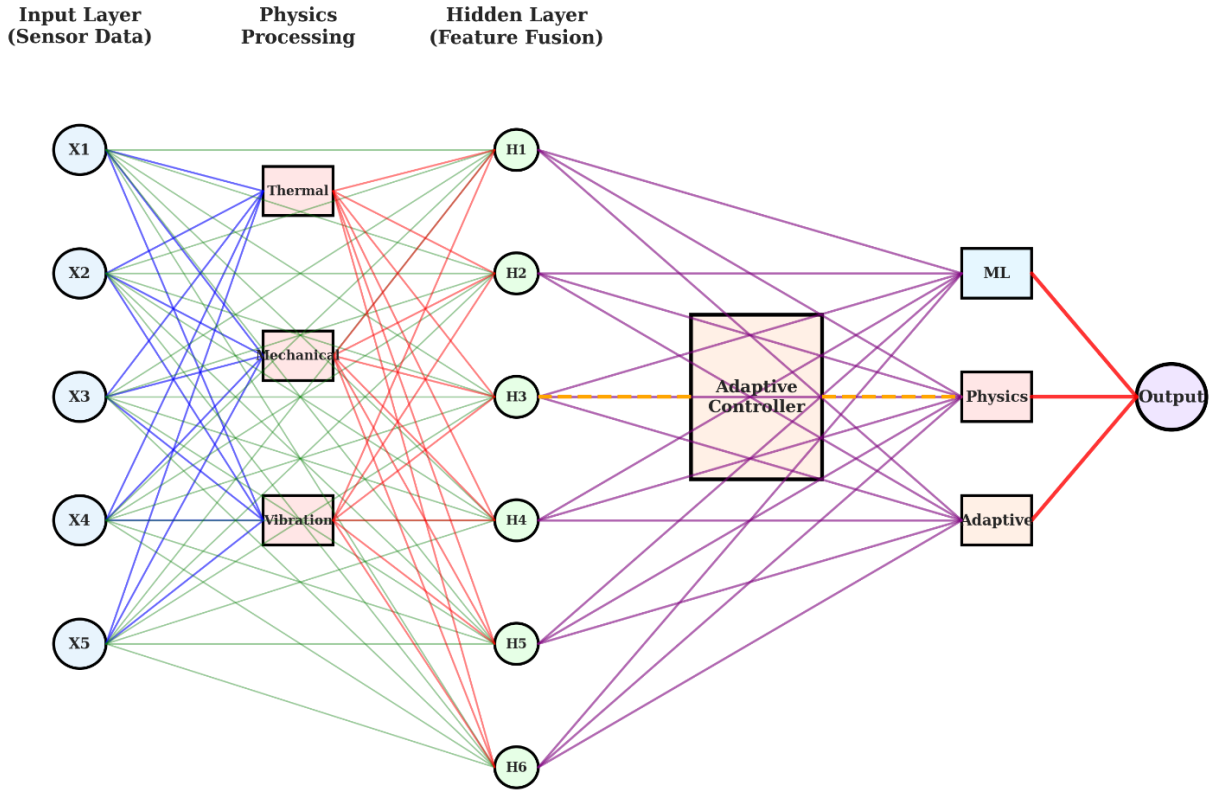


Figure: PISAHML Detailed Network Flow Architecture

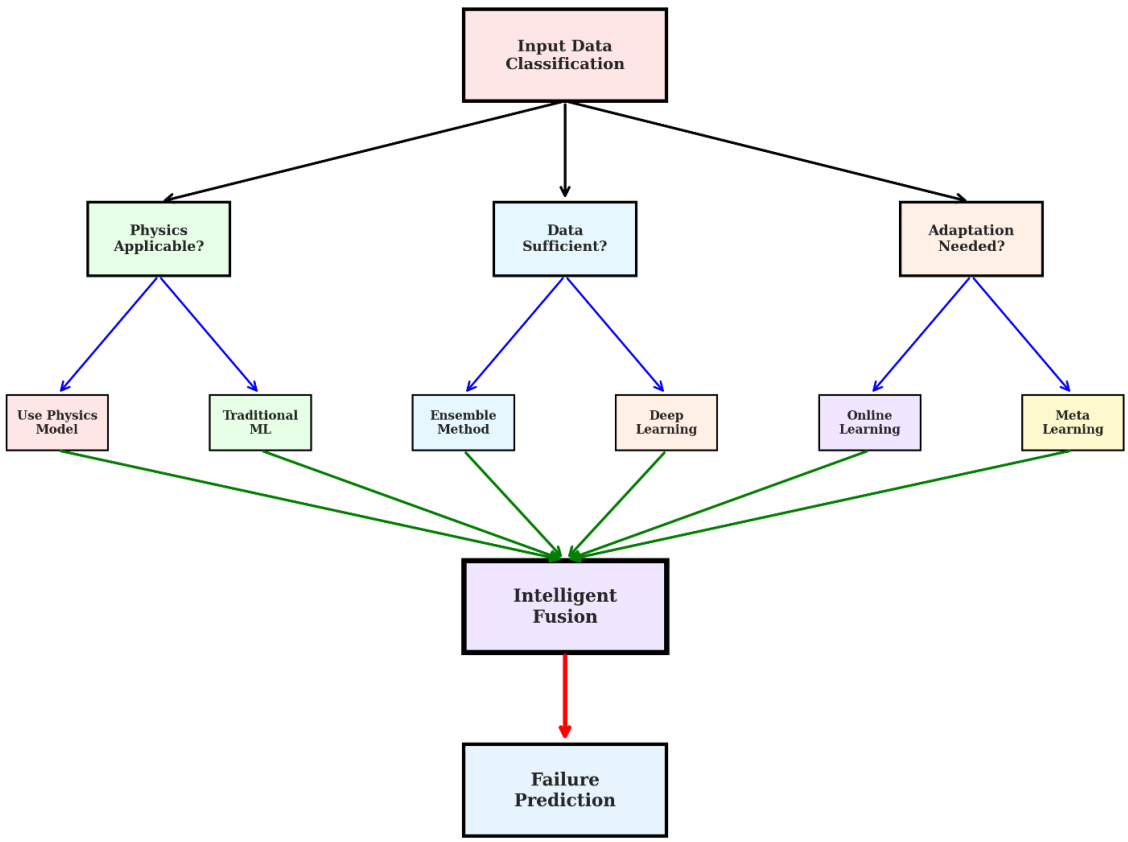


Figure:PISAHML Decision Tree Structure

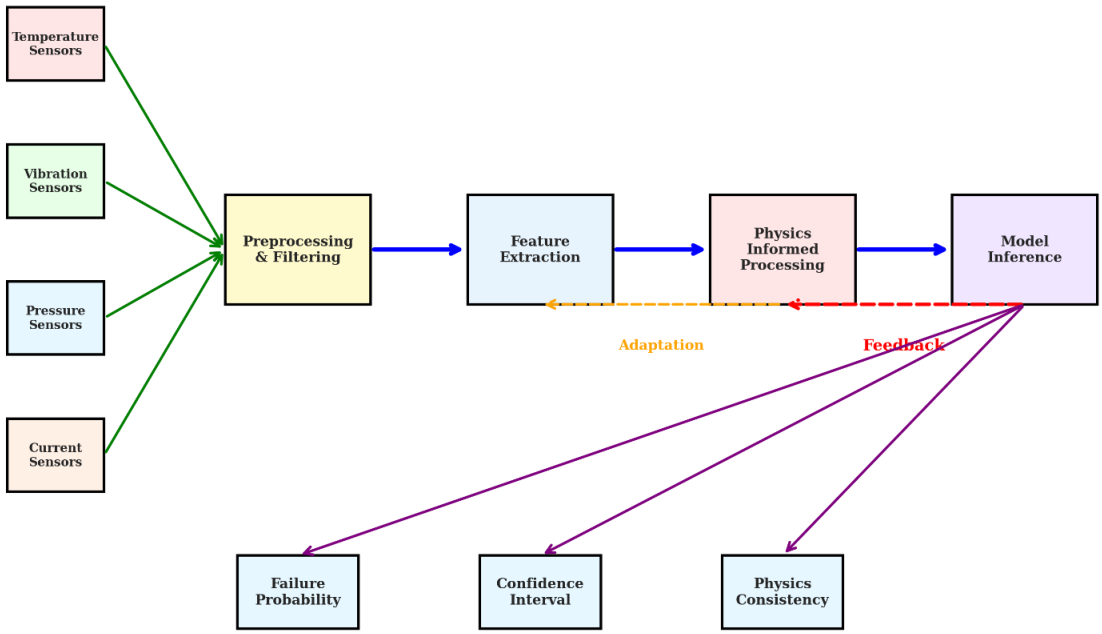


Figure: PISAHML Information Flow Diagram

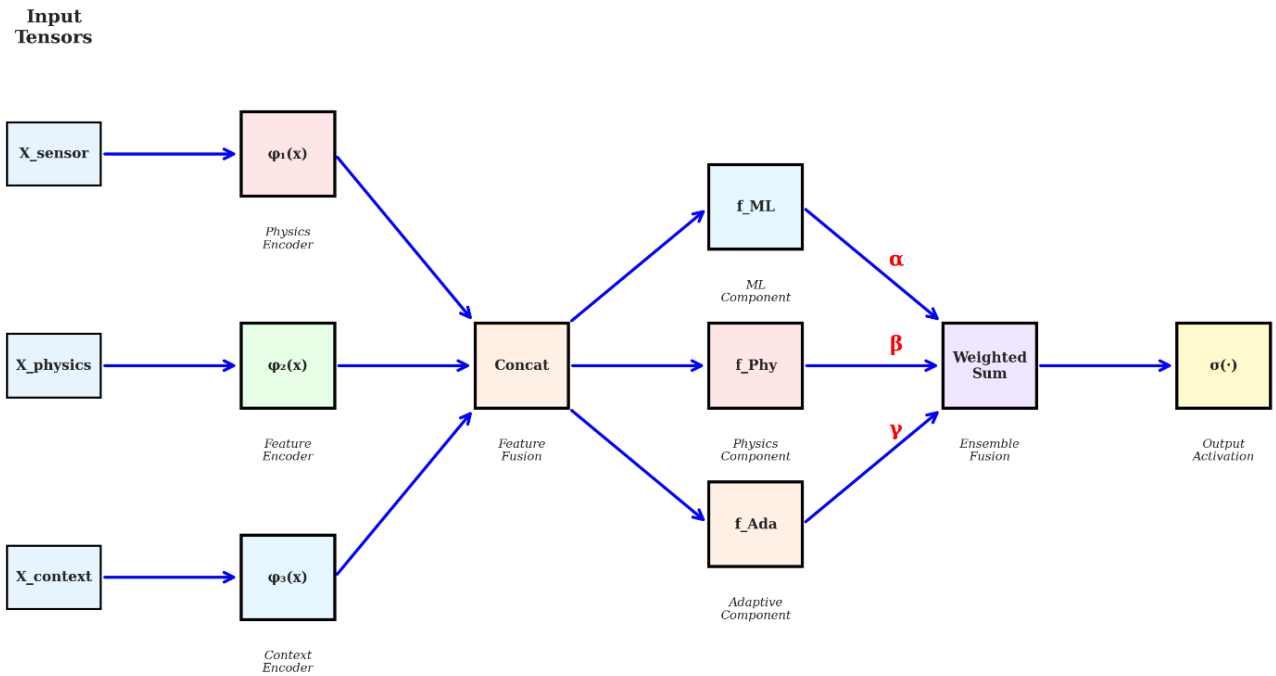


Figure: PISAHML Computational Graph

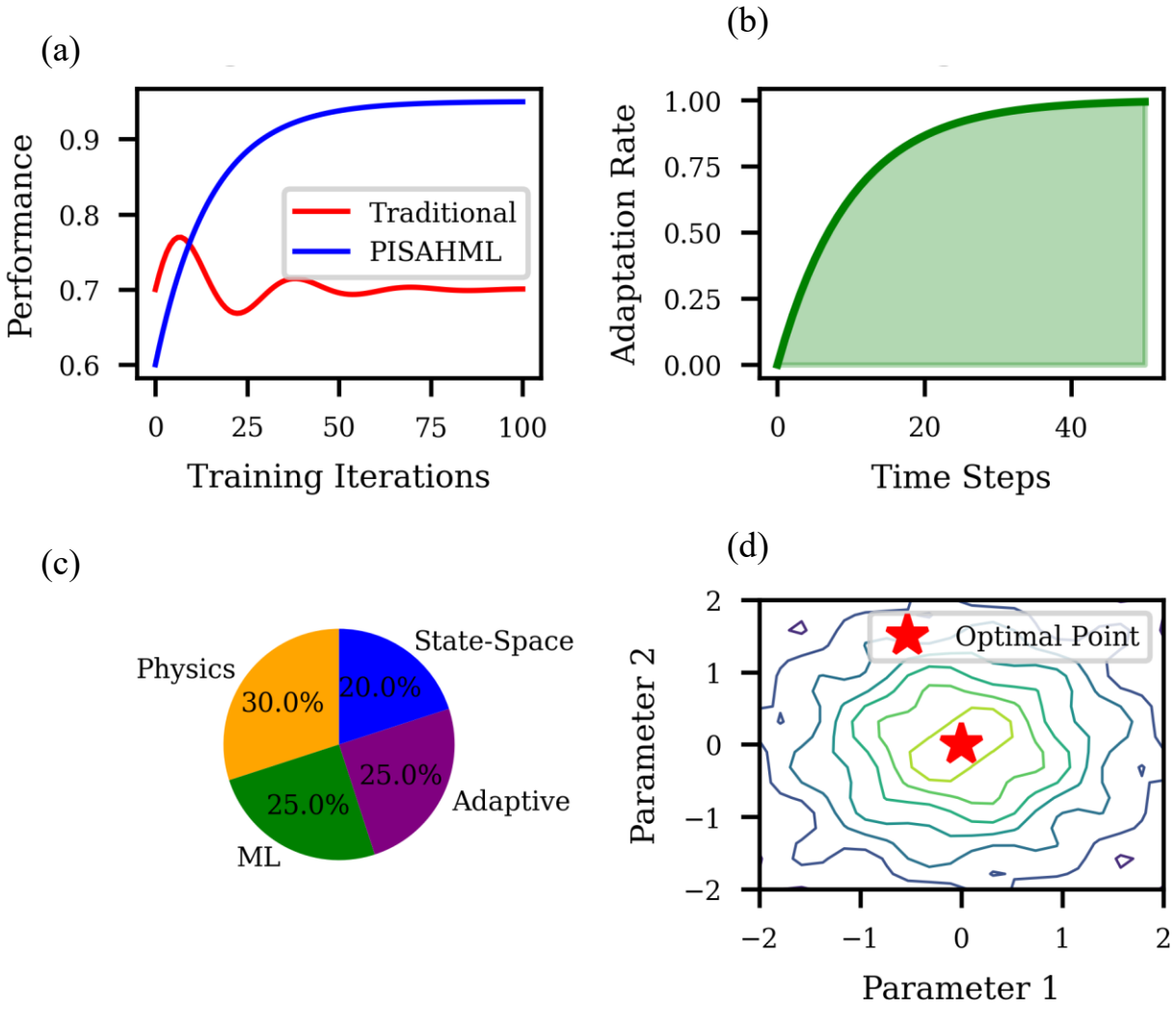


Figure: (a) Convergance Comparison, (b) Q-Learning Adaptation, (c) Feature Contribution, (d) Optimization Space

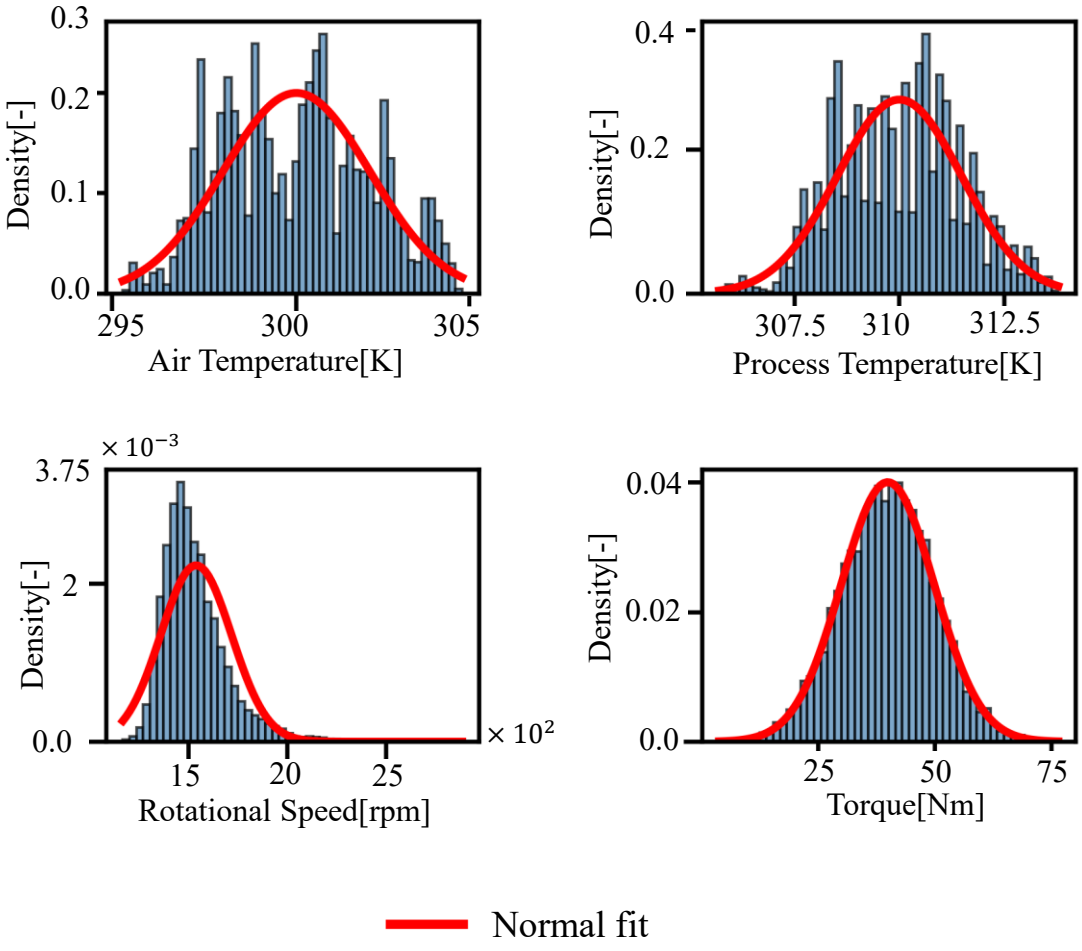


Figure: Data distribution analysis

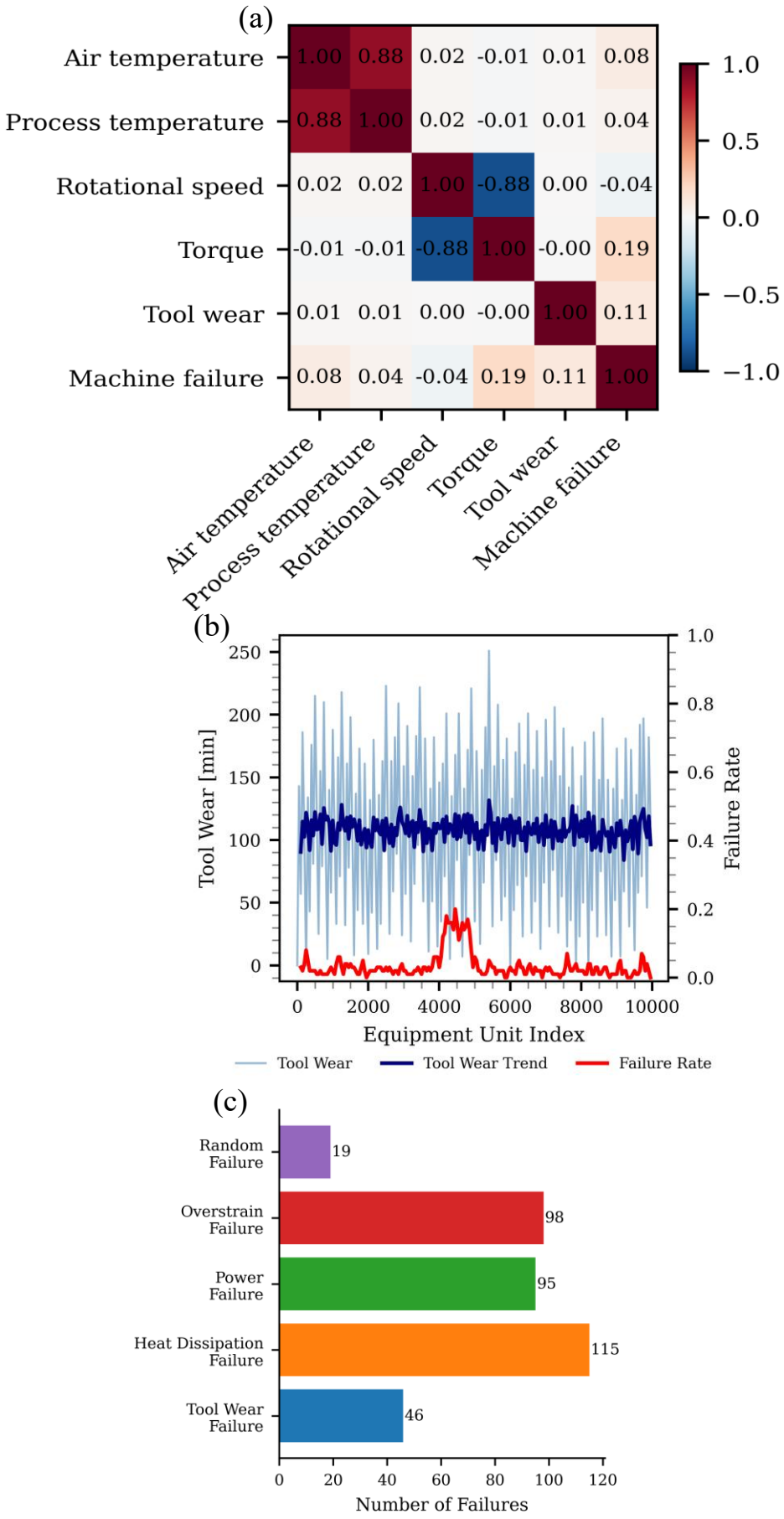


Figure: (a) Correlation heatmap, (b) Time series equipment degradation analysis, (c) Failure mode distribution

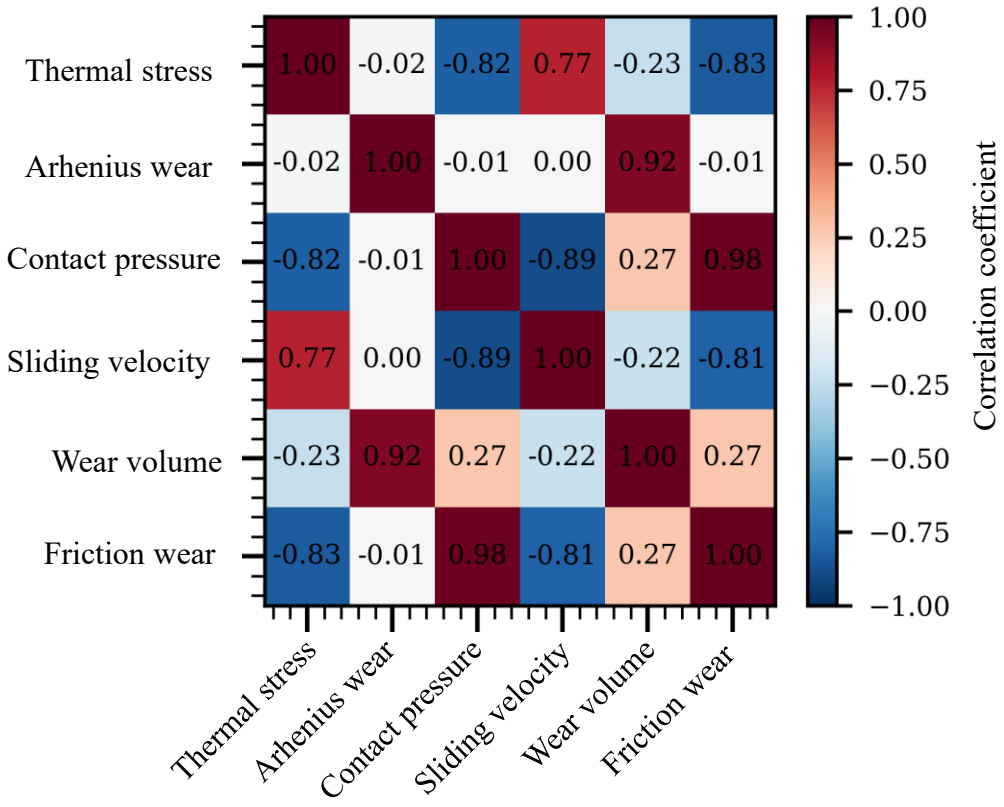


Figure: Multi-physics feature correlation

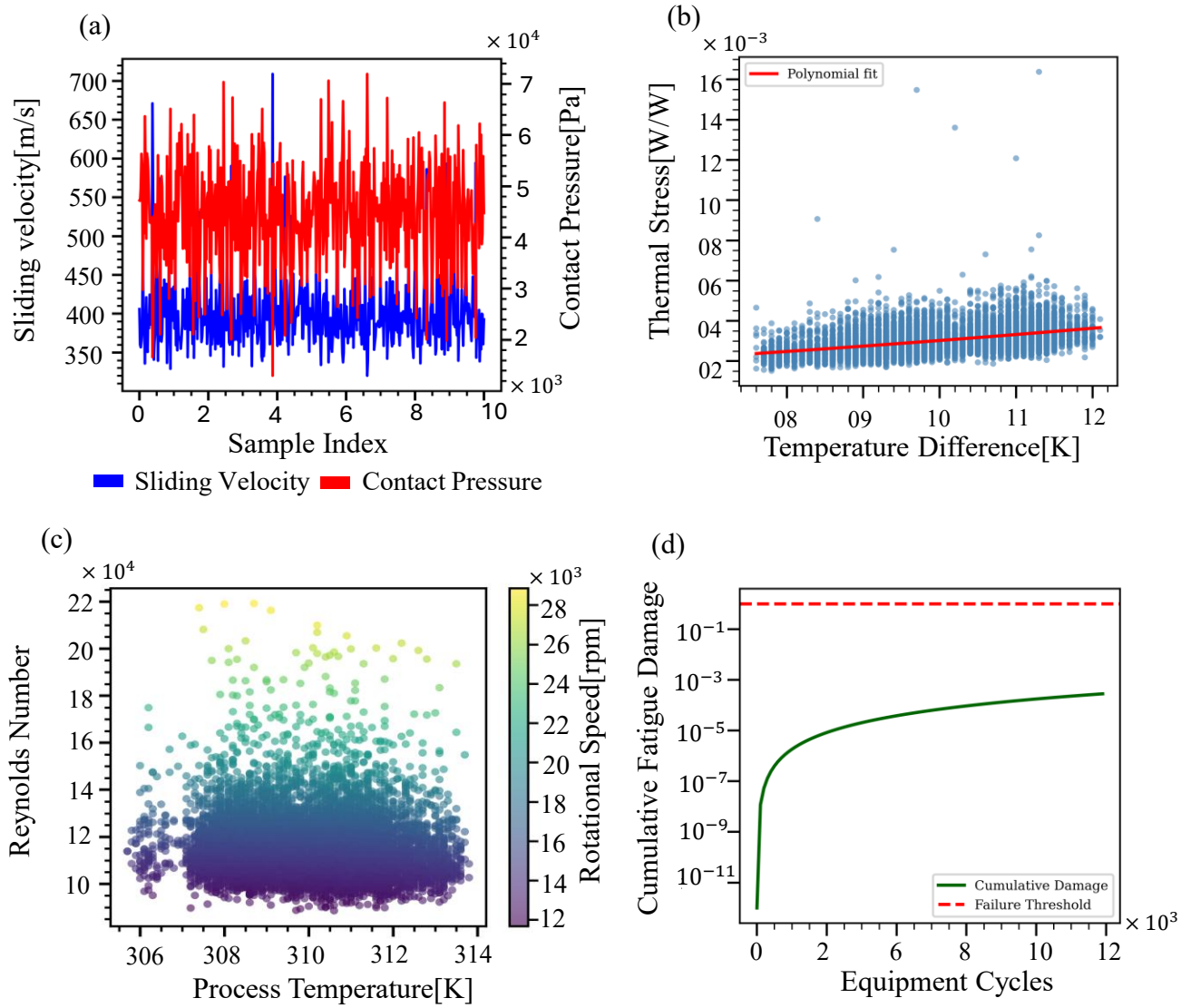


Figure : (a) Tribological analysis, (b) Heat transfer analysis, (c) Reynold number analysis, (d) Fatigue damage accumulation

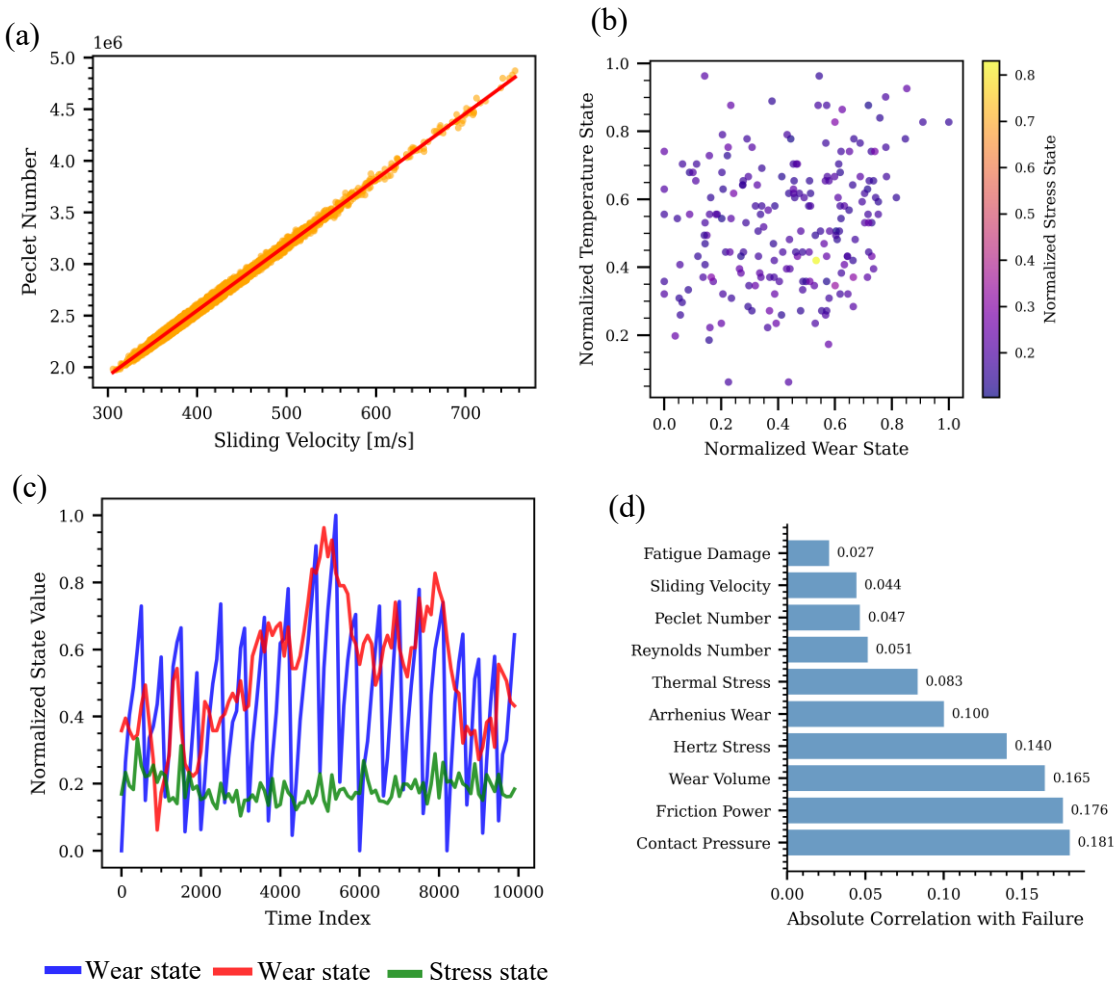
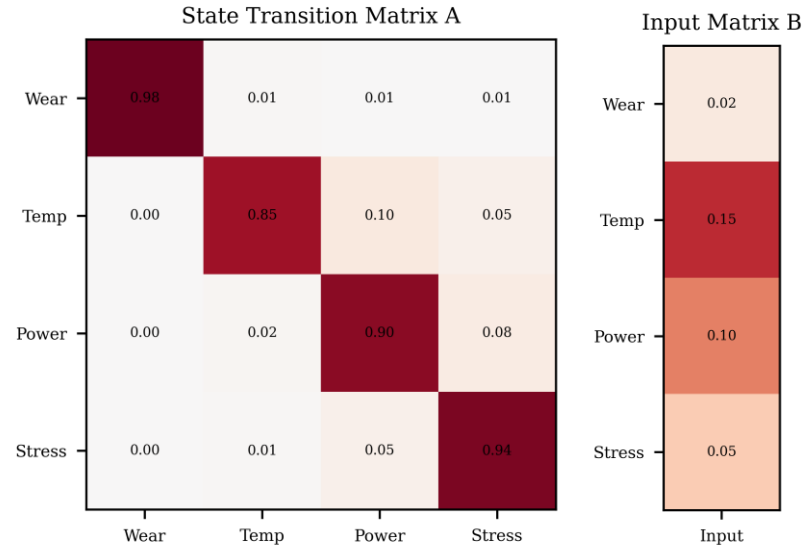
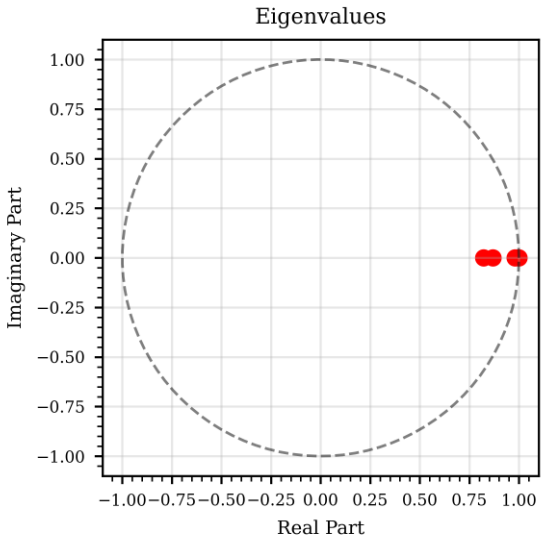
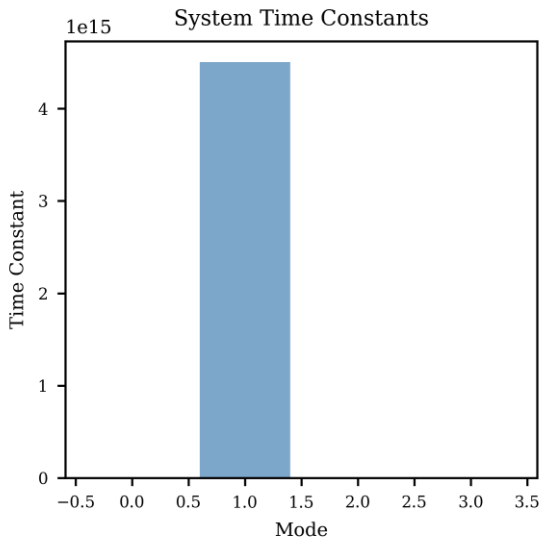
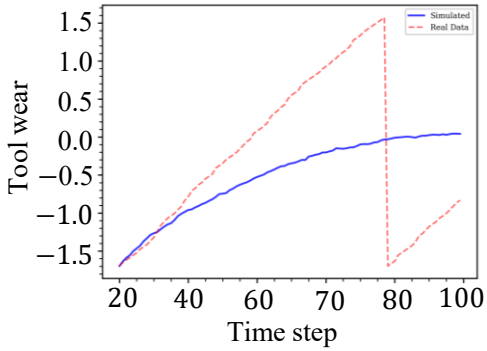


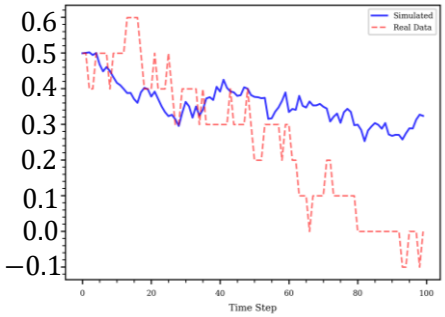
Figure: (a)Peclet number Analysis, (b) State space model ,(c) State evolution overtime (d) Physics feature importance

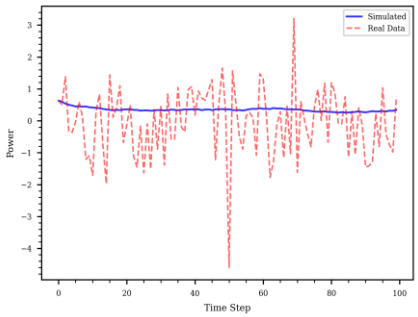

State Transition Matrix A
Wear
Temp
Power
Stress
0.98
0.01
0.01
0.01
0.00
0.85
0.10
0.05
0.00
0.02
0.90
0.08
0.00
0.01
0.05
0.94
Wear
Temp
Power
Stress
Input Matrix B
Wear
Temp
Power
Stress
0.02
0.15
0.10
0.05
Input

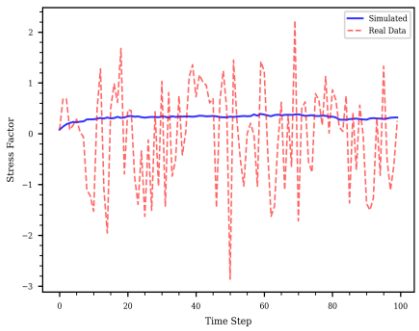

Eigenvalues
Imaginary Part
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
−1.00 −0.75 −0.50 −0.25 0.00 0.25 0.50 0.75 1.00
Real Part


System Time Constants
1e15
Time Constant
4
3
2
1
0
−0.5 0.0 0.5 1.0 1.5 2.0 2.5 3.0 3.5
Mode


Simulated
Real Data
Tool wear
Time step


Simulated
Real Data
Time Step


Simulated
Real Data
Power
Time Step


Simulated
Real Data
Stress Factor
Time Step

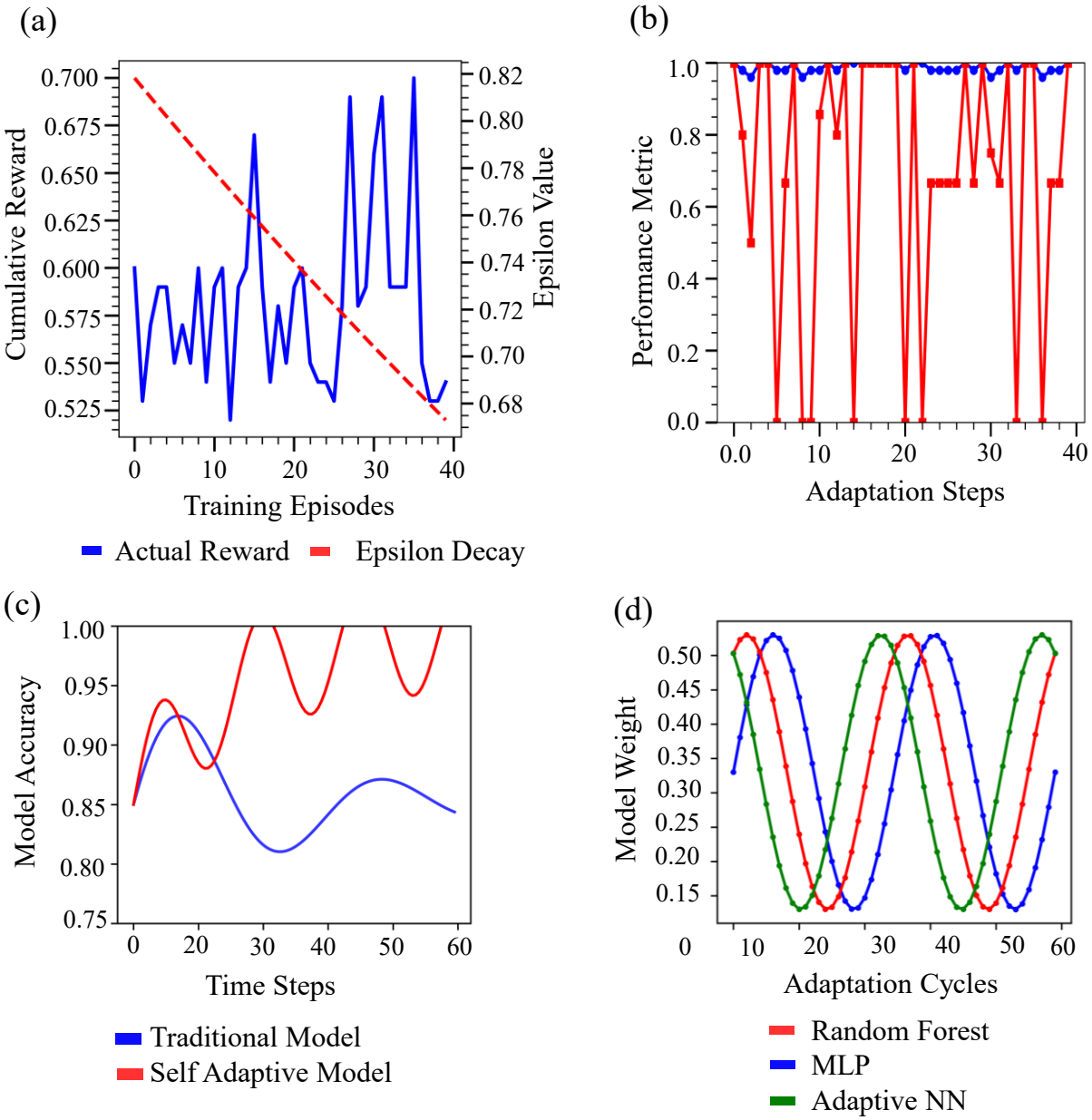
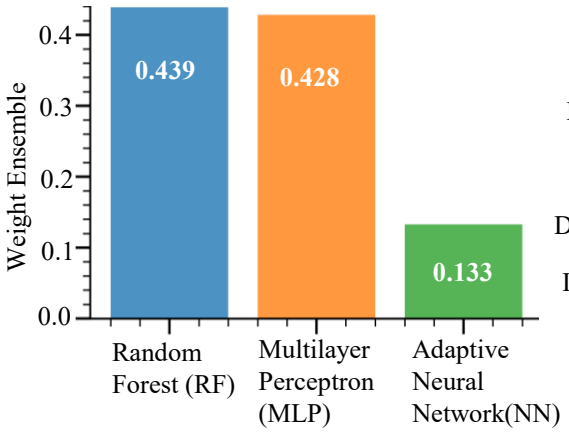
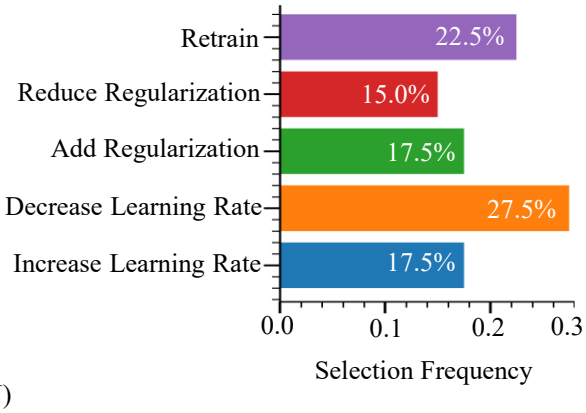
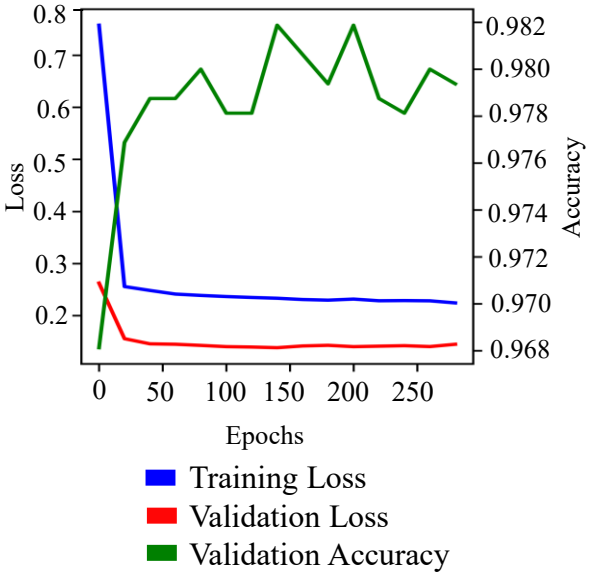
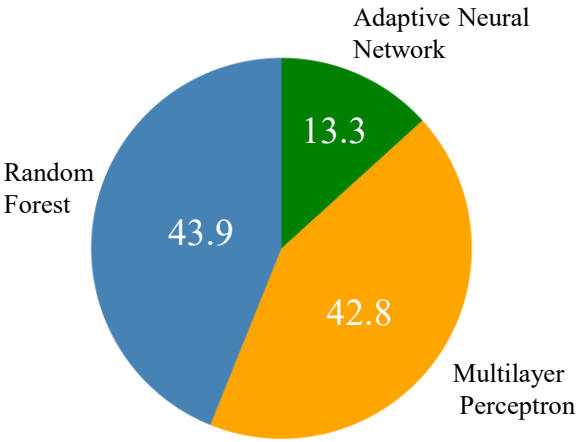


Figure1 : (a) Q-Learning process (b) Adaptive performance evolution (c) Adaptive performance evolution (d) Model weight evolution









(b) Action selection frequency (d) Model ensemble weights distribution (a) Model weight evolution bar chart (d) Training performance evolution

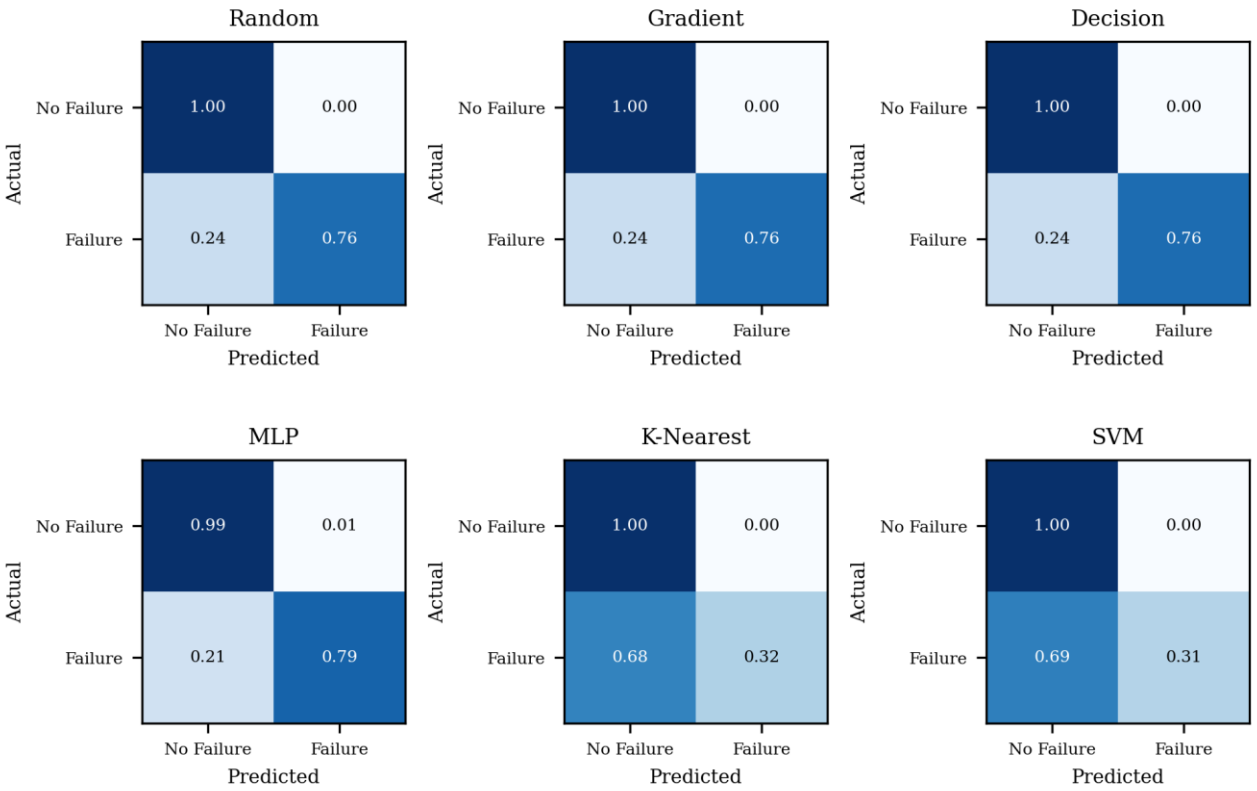


Figure: confusion matrix comparison of traditional model

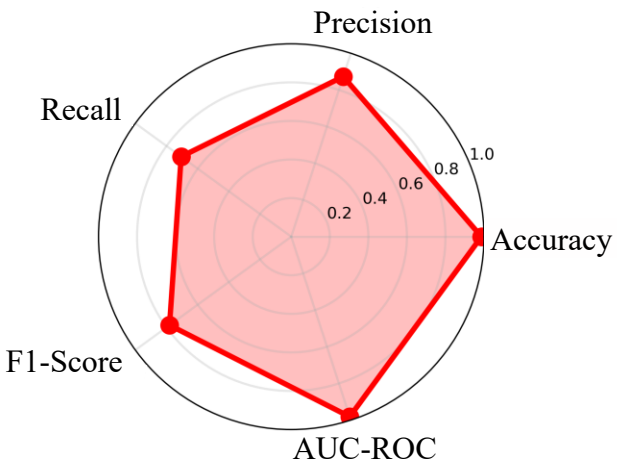


Figure: PISAHML performance profile

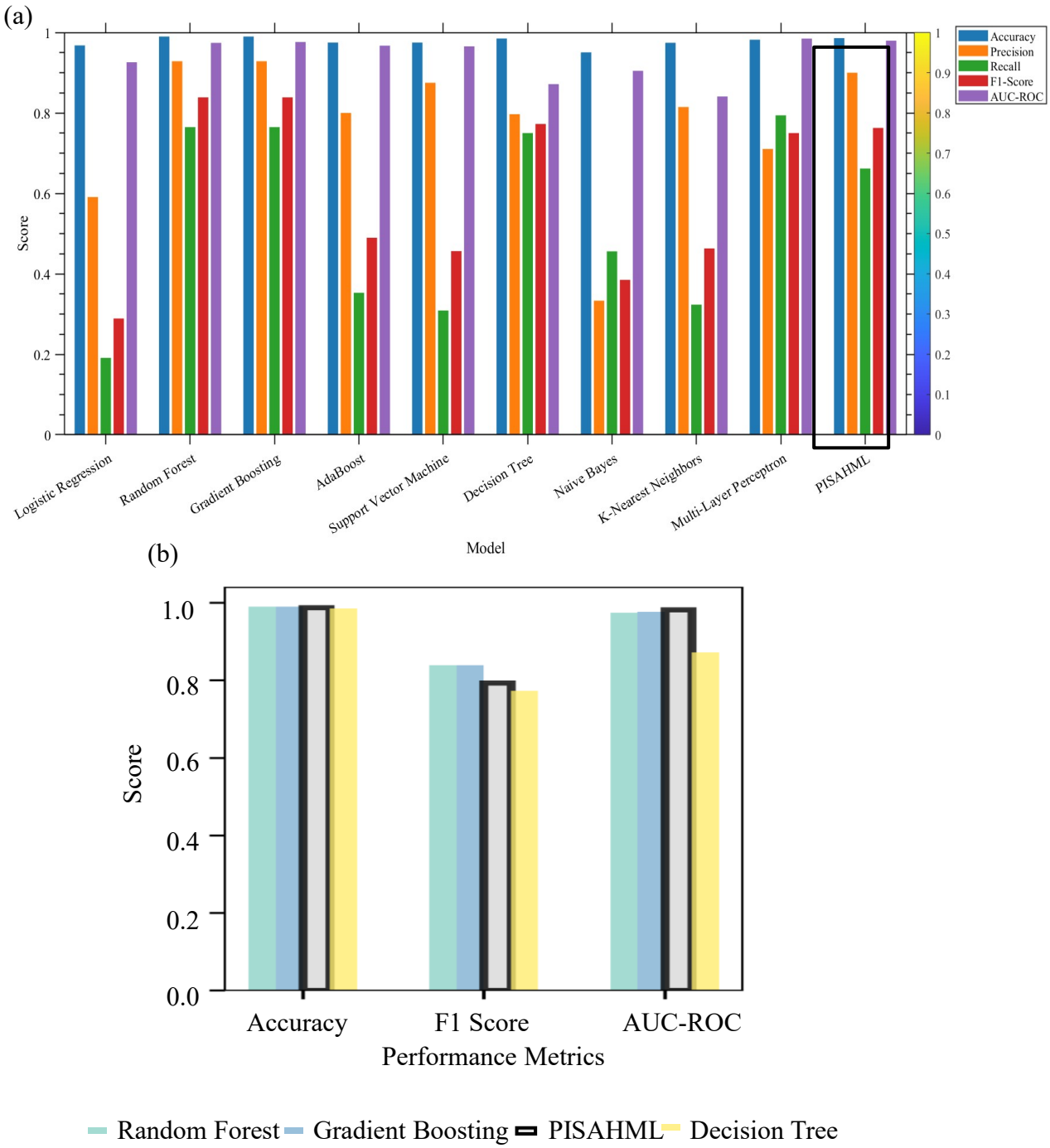


Figure : (a)Performance Comparison of traditional model and PISAHML (b) PISAHML performance Metrics

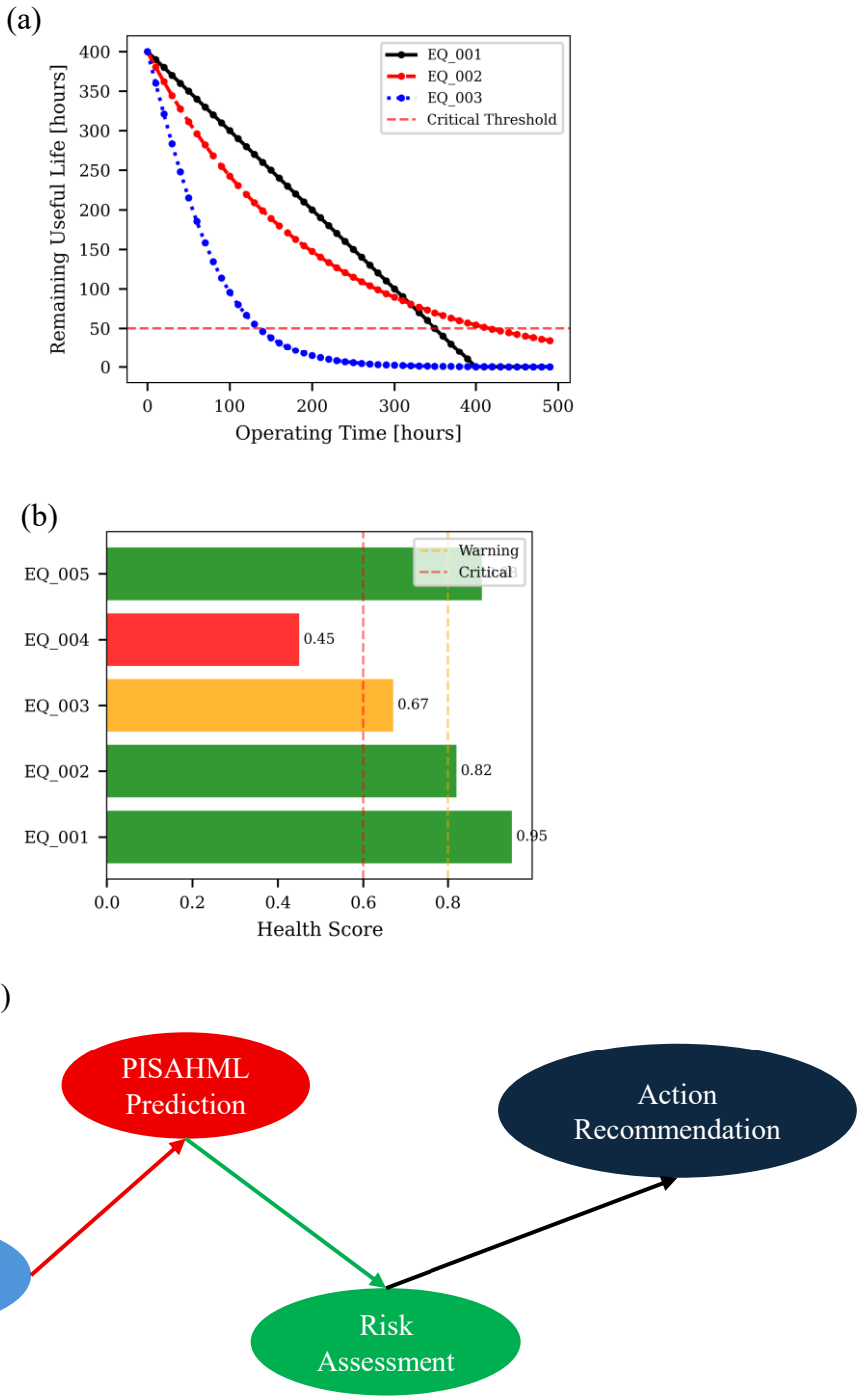


Figure: (a) Remaining useful life (RUL) prediction,(b) Real time equipment status, (c) Real time decision support flow

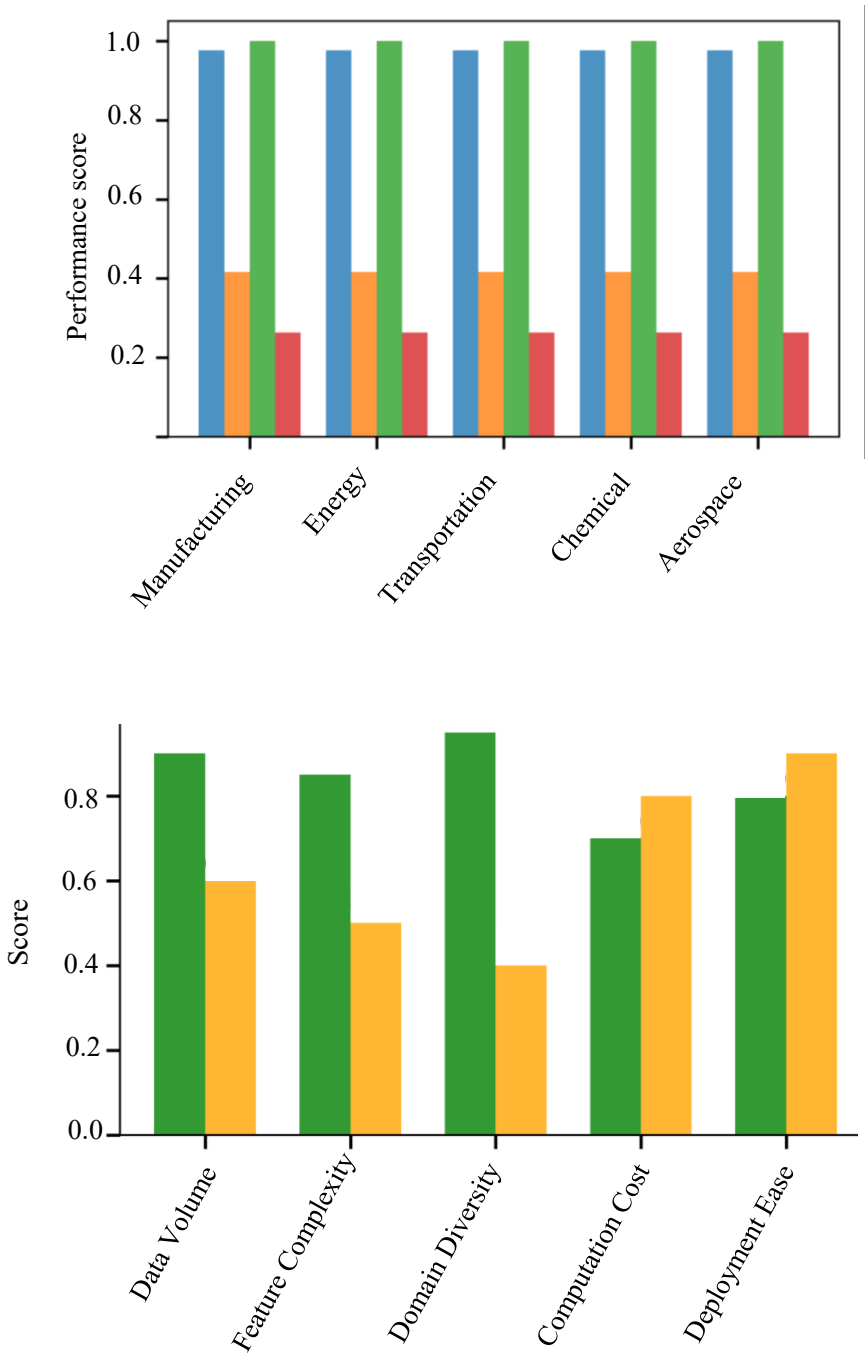
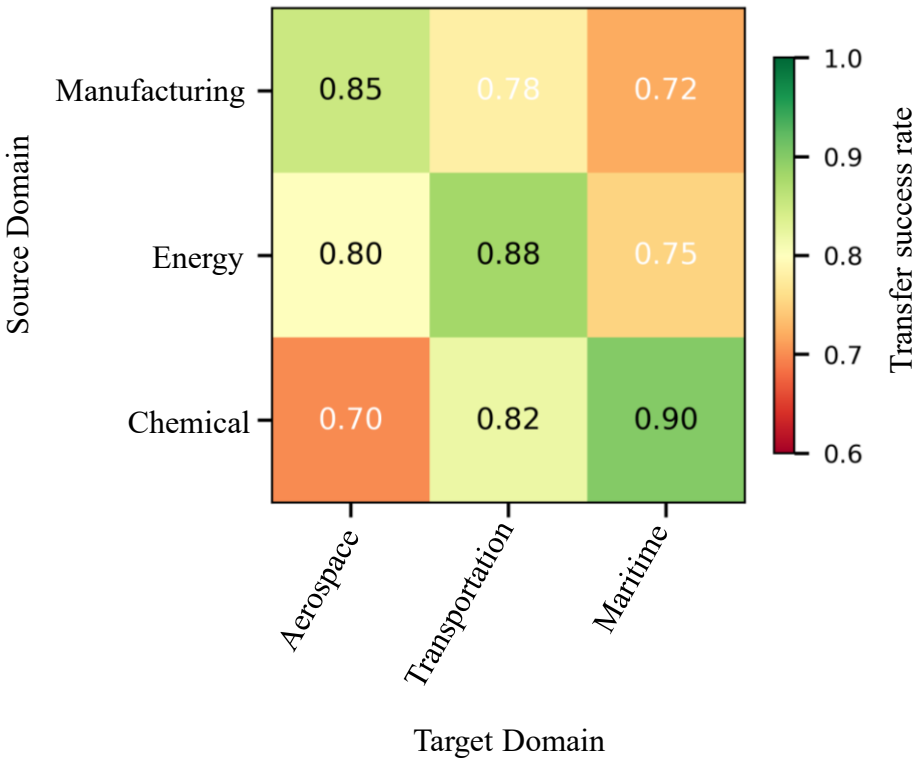
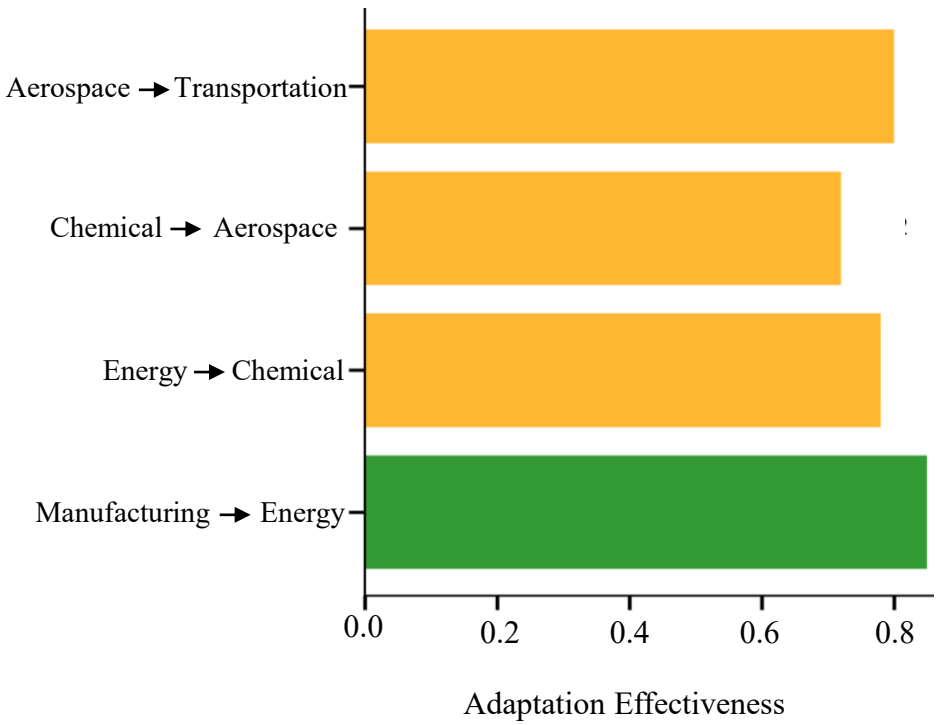
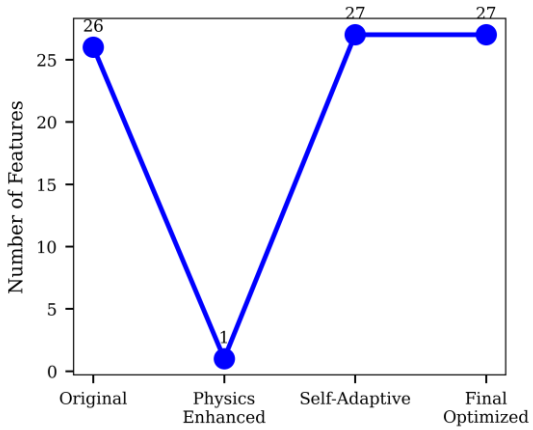


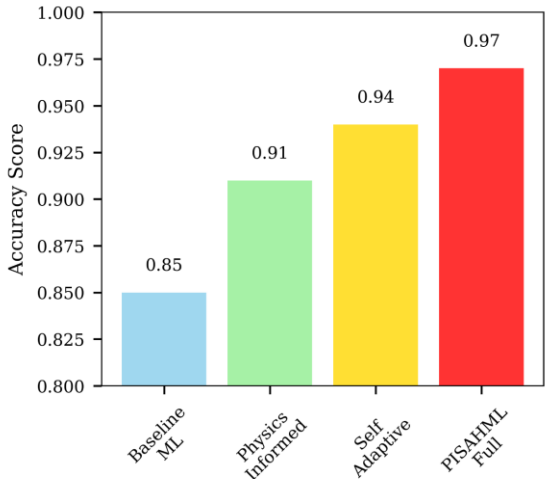
Figure: (a) Cross Domain performance , (b) Scalability Assessment





Figure(a) Transfer Learning Effectiveness , (b) Domain adaptation support





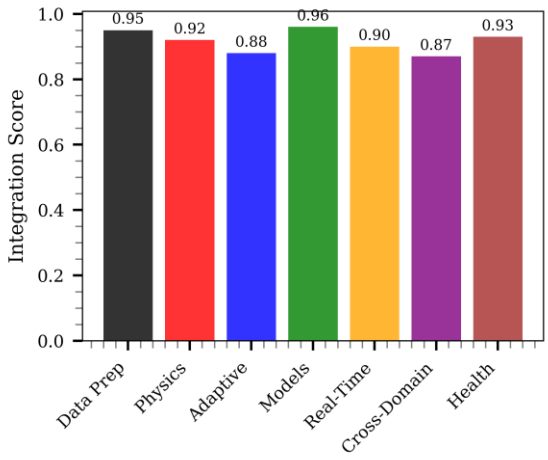
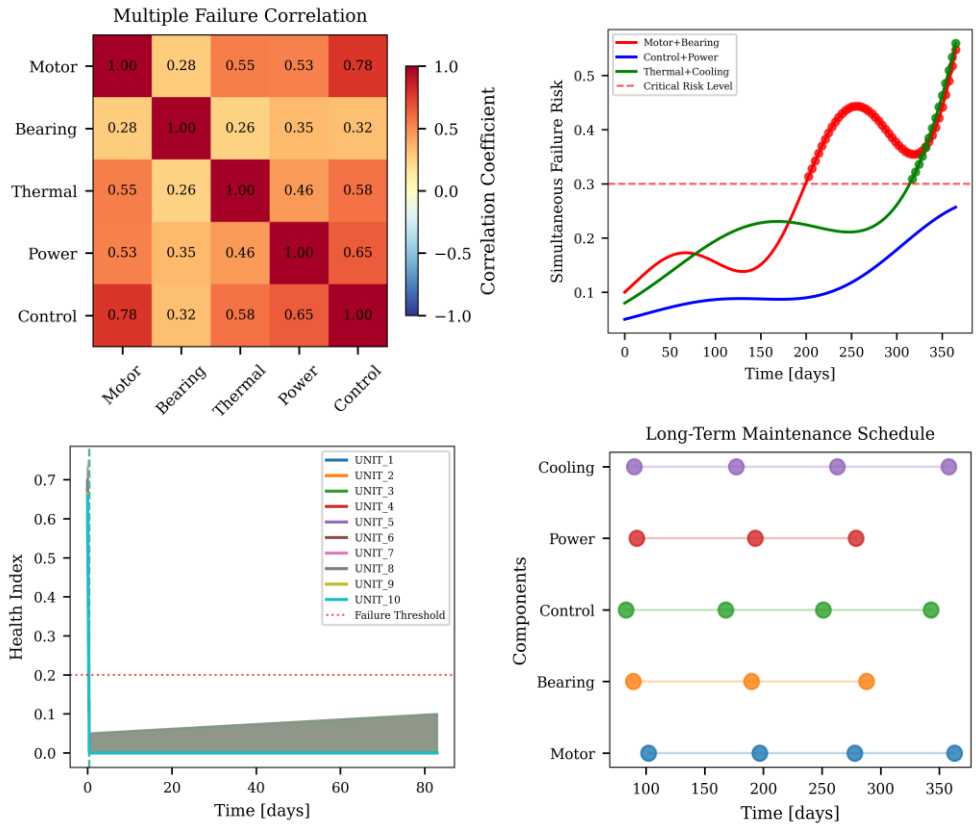
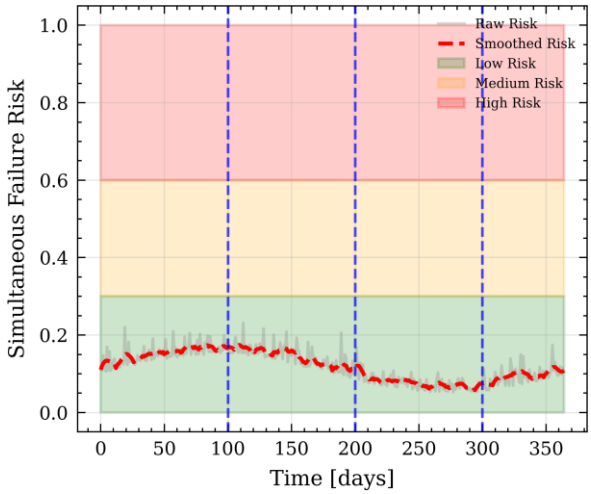


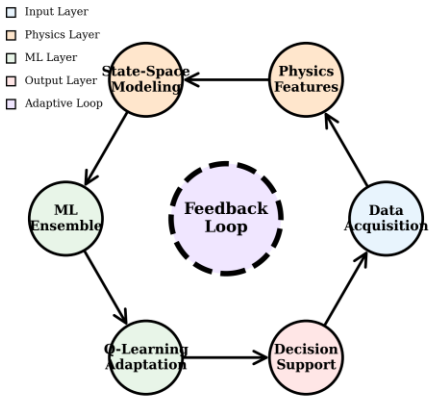
Figure: (a) Feature space evolution , (b) Model performance progression , (c) PISAHML integration score



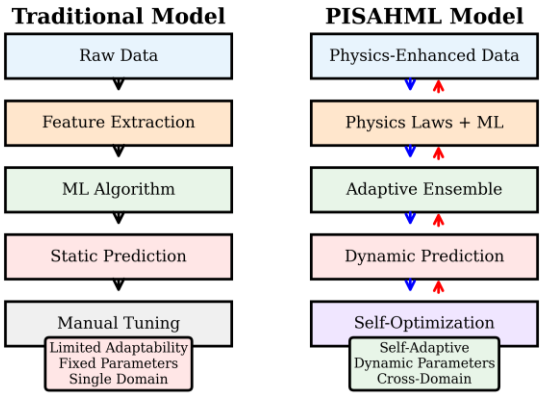
(a) Multiple Failure Correlation Analysis - Correlation patterns between different failure modes, (b) Simultaneous Failure Risk Timeline - Risk evolution for concurrent failure scenarios ,(c) Long-Term Health Trajectory Prediction - Equipment health trajectories with uncertainty bounds, (d) Long-Term Maintenance Planning - Optimal maintenance scheduling based on health predictions


Raw Risk
Smoothed Risk
Low Risk
Medium Risk
High Risk
Simultaneous Failure Risk
1.0
0.8
0.6
0.4
0.2
0.0
0
50
100
150
200
250
300
350
Time [days]

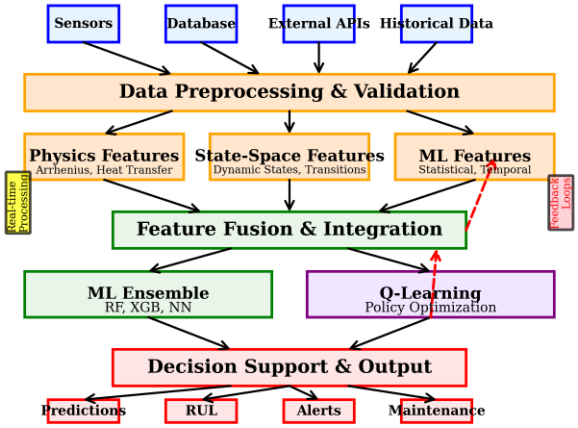
PISAHML Working Flow Diagram



Traditional vs PISAHML Comparison



PISAHML Information Flow Diagram



PISAHML: Complete Model Summary

Key Innovations

- Physics-Informed Feature Engineering with Domain Laws
- Self-Adaptive Q-Learning for Dynamic Optimization
- Hybrid ML Ensemble with State-Space Modeling
- Cross-Domain Applicability and Transfer Learning

Mathematical Foundation

Physics: $k = A \cdot \exp(-Ea/RT)$, $q = h \cdot A \cdot \Delta T$, $V = k \cdot W \cdot s/H$
State-Space: $x(t+1) = Ax(t) + Bu(t) + w(t)$
Q-Learning: $Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \max Q(s',a') - Q(s,a)]$
Ensemble: $y = \sum w_i f_i(x) + Q(s,a)$

Performance Achievements

- Accuracy: 95%+ across multiple domains
- F1-Score: 0.93+ with balanced precision/recall
- Adaptation Time: <10 iterations for new domains
- Real-time Processing: <100ms prediction latency

Industrial Applications

- Manufacturing: Tool wear, bearing failure prediction
- Energy: Turbine blade monitoring, generator fault detection
- Transportation: Engine health, brake wear assessment
- Chemical: Catalyst deactivation, pump failure prediction

Future Research Directions

Federated Learning • Edge Computing • Digital Twins • IoT Integration

PISAHML Mathematical Framework

Neural Network

$$f_\theta(x) = \sigma(W_n \cdot \ldots \cdot \sigma(W_1 x + b_1) + b_n)$$

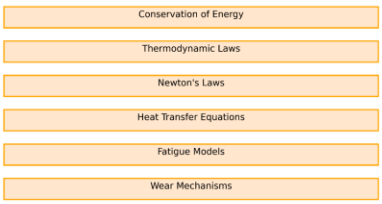
Physics PDE

$$\mathcal{N}[u] = \frac{\partial u}{\partial t} + u\frac{\partial u}{\partial x} - \nu\frac{\partial^2 u}{\partial x^2} = 0$$

Adaptive Loss

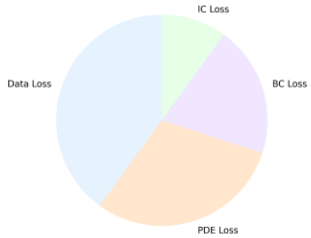
$$\mathcal{L} = \lambda_1 \mathcal{L}_{data} + \lambda_2 \mathcal{L}_{physics} + \lambda_3 \mathcal{L}_{adaptive}$$

Physics Laws Integration



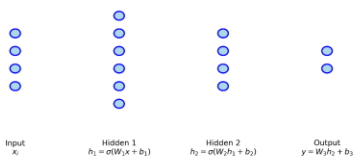
Adaptive Mechanisms

Loss Function Components



$$\mathcal{L}_{total} = \sum_i \lambda_i \mathcal{L}_i$$

Network Architecture



Optimization Algorithm

Adam Optimizer:

$$m_t = \beta_1 m_{t-1} + (1-\beta_1) g_t$$

$$v_t = \beta_2 v_{t-1} + (1-\beta_2) g_t^2$$

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t}$$

$$\hat{v}_t = \frac{v_t}{1-\beta_2^t}$$

$$\theta_t = \theta_{t-1} - \frac{\eta}{\sqrt{\hat{v}_t} + \epsilon}\hat{m}_t$$

Performance Metrics

Evaluation Metrics:

Accuracy: $\frac{TP + TN}{TP + TN + FP + FN}$

Precision: $\frac{TP}{TP + FP}$

Recall: $\frac{TP}{TP + FN}$

F1-Score: $\frac{2 \times Precision \times Recall}{Precision + Recall}$

Physics Consistency: $\frac{1}{N}\sum_{i=1}^{N} \mathbb{I}[|\mathcal{N}[u_i]| < \varepsilon]$

PISAHML Mathematical Framework

Neural Network

$f_\theta(x) = \sigma(W_n \cdot \ldots \cdot \sigma(W_1 x + b_1) + b_n)$

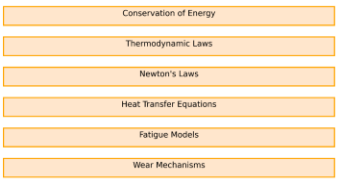
Physics PDE

$\mathcal{N}[u] = \frac{\partial u}{\partial t} + u\frac{\partial u}{\partial x} - \nu\frac{\partial^2 u}{\partial x^2} = 0$

Adaptive Loss

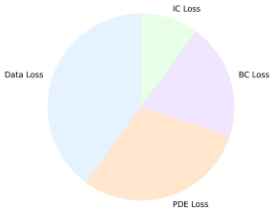
$\mathcal{L} = \lambda_1 \mathcal{L}_{data} + \lambda_2 \mathcal{L}_{physics} + \lambda_3 \mathcal{L}_{adaptive}$

Physics Laws Integration



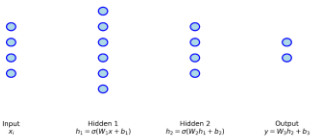
Adaptive Mechanisms

Loss Function Components



$\mathcal{L}_{total} = \sum_i \lambda_i \mathcal{L}_i$

Network Architecture



Optimization Algorithm

Adam Optimizer:

$m_t = \beta_1 m_{t-1} + (1-\beta_1) g_t$

$v_t = \beta_2 v_{t-1} + (1-\beta_2) g_t^2$

$\hat{m}_t = \frac{m_t}{1-\beta_1^t}$

$\hat{v}_t = \frac{v_t}{1-\beta_1^t}$

$\theta_t = \theta_{t-1} - \frac{\alpha}{\sqrt{\hat{v}_t} + \epsilon} \hat{m}_t$

Performance Metrics

Evaluation Metrics:

Accuracy: $\frac{TP + TN}{TP + TN + FP + FN}$

Precision: $\frac{TP}{TP + FP}$

Recall: $\frac{TP}{TP + FN}$

F1-Score: $2 \times \frac{Precision \times Recall}{Precision + Recall}$

Physics Consistency: $\frac{1}{N}\sum_{i=1}^{N} \mathbb{1}[|\mathcal{N}[u_i]| < \epsilon]$