Explicitly modeling risk dynamics improves health status representations

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REASEARCH TRACK

HazardFlow: Enhancing Health Status Representations via Score-based Energy Modeling

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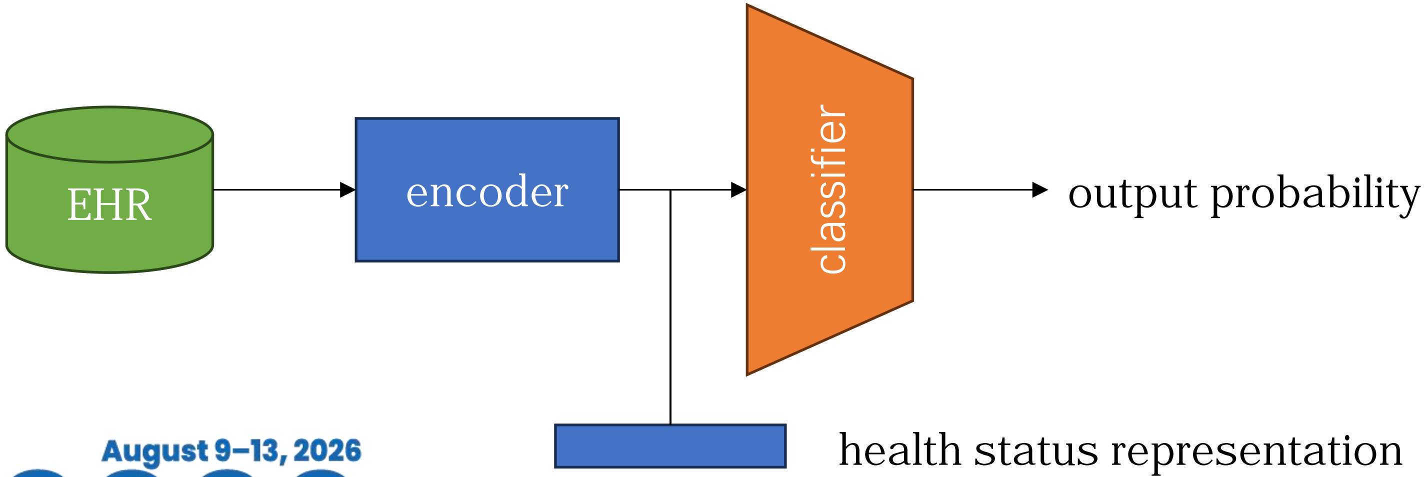
Health Risk Prediction with Electronic Health Records

- EHRs digitize diverse clinical data, including diagnoses, laboratory results, and treatments, providing a comprehensive view of patient health.
- Health risk prediction plays a critical role in early intervention, resource allocation, and clinical decision support by anticipating adverse clinical events.



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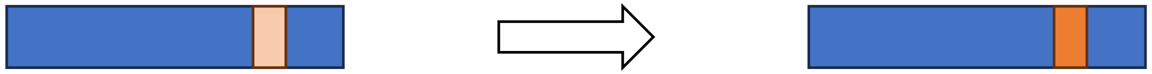
Subtle risk signals are overwhelmed in EHR representations

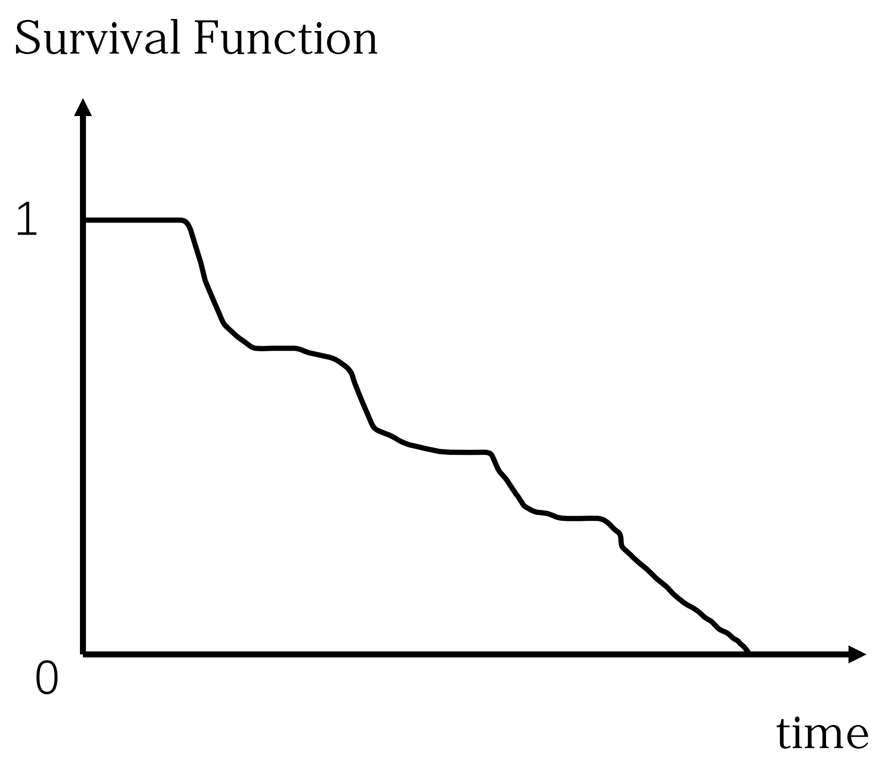
Real-world EHR (Electronic Health Record) data are sparse, irregularly sampled, and highly imbalanced. As a result, learned representations tend to be dominated by majority low-risk patterns, while subtle but critical risk signals remain underrepresented.

Task	**MIMIC-III**		**MIMIC-IV**	
	#label=1	#label=0	#label=1	#label=0
mortality	662	9,055	2,083	123,631

Intuition



If we can identify a risk-related direction in the latent space, we can move health representations along this direction to make risk signals more explicit.



Survival Analysis

Survival Function: $S(t) = 1 - F(t)$. The probability that a person or machine or a business lasts longer than t time units. ($F(t)$: the cumulative distribution function)

Hazard Function: $\lambda(t) = f(t)/S(t)$. The probability that the person or machine or business dies in the next instant, given that it survived to time t. ($f(t)$: the probability density function)

The score function provides a hazard-related direction

Proposition 1 (Score-Hazard Correspondence). Let $\mathbf{x}_t \in \mathbb{R}^{1\times d}$ denote a health status representation at time t, with marginal distribution $p_t(\mathbf{x})$. Suppose the survival function $S(t)$ is learned by $1-\psi(\mathbf{x}_t)$, and there exists a learned mapping from $\mathbf{x}_t$ to a dynamic hazard vector $\mathbf{h}_t \in \mathbb{R}^{1\times d}$, which denotes the corresponding hazard function $h(t)$. Then, the time-dependent score function $\nabla_{\mathbf{x}} \log p_t(\mathbf{x})$ is approximately proportional to the hazard,

$$\mathbf{h}_t \approx \alpha(t) \nabla_{\mathbf{x}} \log p_t(\mathbf{x}),$$

where $\alpha(t)$ is a scalar function of time.

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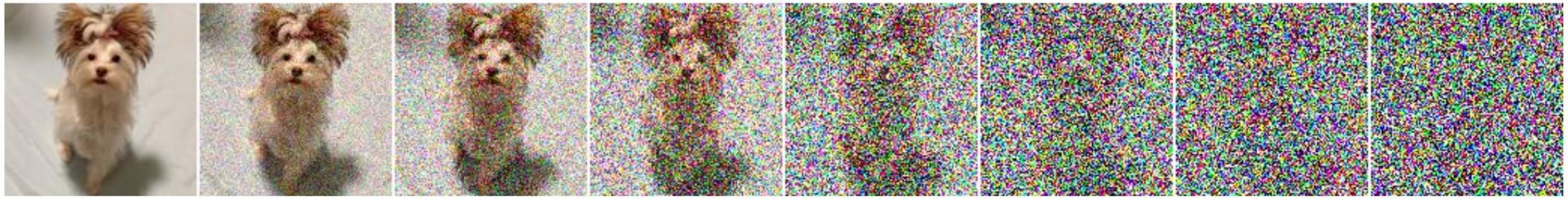
Score-based Generative Modeling

Forward SDE (data → noise)

$$\mathbf{x}(0) \longrightarrow \mathrm{d}\mathbf{x} = \mathbf{f}(\mathbf{x}, t)\mathrm{d}t + g(t)\mathrm{d}\mathbf{w} \longrightarrow \mathbf{x}(T)$$



score function

$$\mathbf{x}(0) \longleftarrow \mathrm{d}\mathbf{x} = \left[\mathbf{f}(\mathbf{x}, t) - g^2(t)\boxed{\nabla_{\mathbf{x}} \log p_t(\mathbf{x})}\right] \mathrm{d}t + g(t)\mathrm{d}\bar{\mathbf{w}} \longleftarrow \mathbf{x}(T)$$

Reverse SDE (noise → data)

https://yang-song.net/blog/2021/score/

Survival Energy Hypothesis (SEH) [Shimizu et al., 2021]. SEH models mortality as the depletion of a latent quantity termed *survival energy*, which can be modeled as a drifted Brownian motion:

$$E_t = E_c + f_c t + g_c w_t.$$

Score-based Energy Modeling. To characterize the Brownian motion in SEH, we use $\mathbf{x}_t$ to encode the survival energy, and model $\mathrm{d}\mathbf{x}_t$ using a diffusion process, governed by the following SDE:

$$\mathrm{d}\mathbf{x}_t = f(\mathbf{x}_t, t)\mathrm{d}t + g(t)\mathrm{d}w_t.$$

Probability Flow Ordinary Differential Equation. We express the reverse process using a probability-flow ODE:

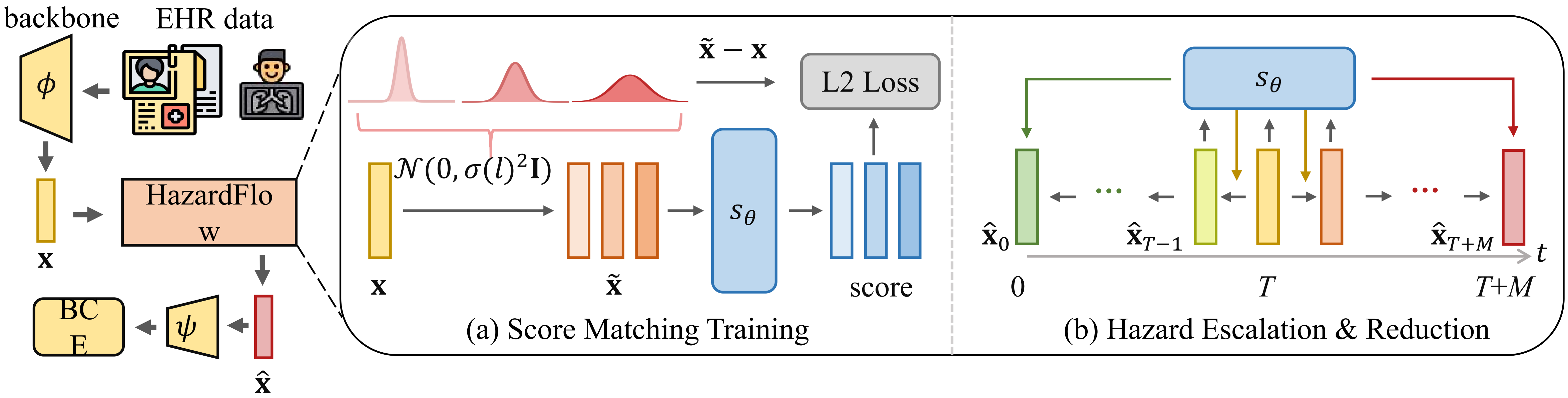
$$\mathrm{d}\mathbf{x}_t = [f(\mathbf{x}_t, t)\mathrm{d}t - g(t)^2 \nabla_{\mathbf{x}} \log p_t(\mathbf{x})]\mathrm{d}t.$$

We omit the drift term and discretize the continuous denoising process using annealed Langevin dynamics:

$$x_{i+1} = x_i + \frac{\epsilon}{2} g(i)^2 \nabla_{\mathbf{x}} \log p_i(\mathbf{x}).$$

This iterative step can be regarded as enhancing the representation toward a higher-risk state.

HazardFlow



HazardFlow refines backbone representations through two steps:

Step 1: Train a score network using denoising score matching.

$$\mathcal{L}_{SM} = \mathbb{E}_l \left\{ \lambda(l) \mathbb{E}_{p(\mathbf{x})} \mathbb{E}_{q_l(\tilde{\mathbf{x}}|\mathbf{x})} \left[\| s_\theta(\tilde{\mathbf{x}}, l) + \frac{\tilde{\mathbf{x}} - \mathbf{x}}{\delta(l)^2} \|_2^2 \right] \right\}$$

Step 2: Iteratively add or subtract the learned score to obtain higher- or lower-risk representations.

$$\hat{\mathbf{x}}_{T+i+1} = \hat{\mathbf{x}}_{T+i} + \frac{\sigma^{2i}\epsilon}{2} s_\theta(\hat{\mathbf{x}}_{T+i}, i) \qquad \hat{\mathbf{x}}_{i-1} = \hat{\mathbf{x}}_i - \frac{\sigma^{2i}\epsilon}{2} s_\theta(\hat{\mathbf{x}}_i, i)$$

Method	mortality				readmission			
	MIMIC-III		MIMIC-IV		MIMIC-III		MIMIC-IV	
	PRAUC	AUROC	PRAUC	AUROC	PRAUC	AUROC	PRAUC	AUROC
ConCare	$11.76_{\pm 1.13}$	$61.08_{\pm 2.47}$	$4.18_{\pm 0.34}$	$71.00_{\pm 0.80}$	$67.75_{\pm 3.47}$	$64.44_{\pm 2.05}$	$68.12_{\pm 0.39}$	$67.54_{\pm 0.36}$
ConCare w/ HF	$\mathbf{25.22}_{\pm 7.47}$	$\mathbf{75.65}_{\pm 7.47}$	$\mathbf{4.59}_{\pm 0.68}$	$\mathbf{72.60}_{\pm 1.37}$	$\mathbf{71.82}_{\pm 3.96}$	$\mathbf{68.37}_{\pm 4.90}$	$\mathbf{69.18}_{\pm 2.25}$	$\mathbf{68.26}_{\pm 1.54}$
StageNet	$34.21_{\pm 34.83}$	$69.08_{\pm 18.59}$	$3.26_{\pm 0.32}$	$66.19_{\pm 1.97}$	$62.56_{\pm 2.40}$	$61.06_{\pm 1.88}$	$68.70_{\pm 2.99}$	$67.72_{\pm 2.39}$
StageNet w/ HF	$\mathbf{39.29}_{\pm 18.92}$	$\mathbf{77.80}_{\pm 13.48}$	$\mathbf{3.54}_{\pm 0.21}$	$\mathbf{67.28}_{\pm 1.99}$	$\mathbf{66.46}_{\pm 3.81}$	$\mathbf{64.88}_{\pm 3.88}$	$\mathbf{70.76}_{\pm 2.91}$	$\mathbf{69.48}_{\pm 2.22}$
TCN	$13.45_{\pm 5.77}$	$61.32_{\pm 7.78}$	$3.09_{\pm 0.33}$	$65.66_{\pm 2.22}$	$63.53_{\pm 2.23}$	$60.70_{\pm 1.59}$	$67.12_{\pm 0.48}$	$66.70_{\pm 0.38}$
TCN w/ HF	$\mathbf{17.46}_{\pm 9.21}$	$\mathbf{65.08}_{\pm 8.03}$	$\mathbf{3.15}_{\pm 0.26}$	$\mathbf{66.77}_{\pm 2.18}$	$\mathbf{65.36}_{\pm 3.32}$	$\mathbf{62.34}_{\pm 3.40}$	$\mathbf{67.29}_{\pm 0.40}$	$\mathbf{66.81}_{\pm 0.42}$
GRASP	$12.34_{\pm 5.09}$	$60.24_{\pm 6.50}$	$3.48_{\pm 0.31}$	$67.84_{\pm 2.31}$	$64.77_{\pm 2.81}$	$61.76_{\pm 2.40}$	$67.57_{\pm 0.44}$	$67.07_{\pm 0.35}$
GRASP w/ HF	$\mathbf{14.68}_{\pm 5.35}$	$\mathbf{63.67}_{\pm 7.33}$	$\mathbf{5.03}_{\pm 1.78}$	$\mathbf{70.09}_{\pm 3.45}$	$\mathbf{66.47}_{\pm 1.96}$	$\mathbf{63.68}_{\pm 1.80}$	$\mathbf{68.87}_{\pm 2.29}$	$\mathbf{68.12}_{\pm 1.56}$
AdaCare	$51.42_{\pm 36.06}$	$77.52_{\pm 18.31}$	$3.10_{\pm 1.22}$	$64.79_{\pm 3.63}$	$64.60_{\pm 2.28}$	$63.45_{\pm 2.77}$	$66.78_{\pm 0.78}$	$66.62_{\pm 0.59}$
AdaCare w/ HF	$\mathbf{58.88}_{\pm 31.77}$	$\mathbf{79.99}_{\pm 16.83}$	$\mathbf{4.60}_{\pm 2.72}$	$\mathbf{66.06}_{\pm 5.41}$	$\mathbf{68.75}_{\pm 5.72}$	$\mathbf{68.05}_{\pm 5.14}$	$\mathbf{68.07}_{\pm 1.37}$	$\mathbf{67.71}_{\pm 1.77}$

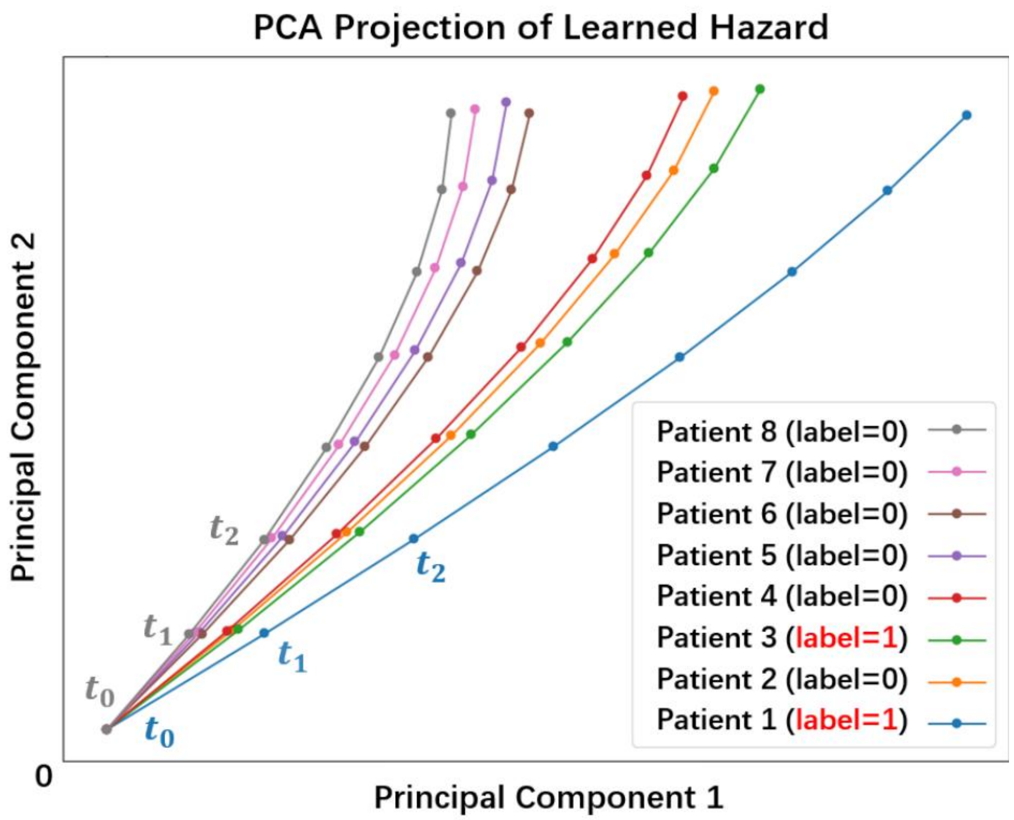
HazardFlow consistently improves five uni-modal backbones across mortality and readmission tasks.

Method	**mortality**		**phenotyping**	
	PRAUC	AUROC	PRAUC	AUROC
MedFuse	$49.39_{\pm1.41}$	$85.16_{\pm0.21}$	$41.78_{\pm0.26}$	$76.31_{\pm0.18}$
MedFuse w/ HF	$\mathbf{51.58_{\pm2.22}}$	$\mathbf{85.51_{\pm0.38}}$	$\mathbf{41.91_{\pm0.13}}$	$\mathbf{76.44_{\pm0.09}}$
DrFuse	$41.70_{\pm1.96}$	$79.18_{\pm1.54}$	$\mathbf{39.02_{\pm0.18}}$	$72.38_{\pm0.22}$
DrFuse w/ HF	$\mathbf{42.77_{\pm2.49}}$	$\mathbf{80.42_{\pm1.37}}$	$39.00_{\pm0.21}$	$\mathbf{72.45_{\pm0.09}}$
DDL-CXR	$44.92_{\pm0.68}$	$80.01_{\pm0.74}$	$43.58_{\pm1.20}$	$71.71_{\pm0.70}$
DDL-CXR w/ HF	$\mathbf{46.26_{\pm1.36}}$	$\mathbf{80.59_{\pm0.41}}$	$\mathbf{44.53_{\pm0.20}}$	$\mathbf{72.49_{\pm0.31}}$

11 of 12 multi-modal metrics improved.

	PRAUC	**AUROC**
MedFuse	$49.39_{\pm1.41}$	$85.16_{\pm0.21}$
MedFuse w/ HF	$50.20_{\pm0.72}$	$\mathbf{85.87_{\pm0.26}}$
MeduFuse w/ HF+	$\mathbf{50.70_{\pm0.86}}$	$85.73_{\pm0.24}$
DrFuse	$41.70_{\pm1.96}$	$79.18_{\pm1.54}$
DrFuse w/ HF	$48.24_{\pm0.74}$	$\mathbf{83.39_{\pm0.27}}$
DrFuse w/ HF+	$\mathbf{48.36_{\pm0.73}}$	$83.37_{\pm0.28}$
DDL-CXR	$44.92_{\pm0.68}$	$80.01_{\pm0.74}$
DDL-CXR w/ HF	$44.99_{\pm0.49}$	$80.44_{\pm0.39}$
DDL-CXR w/ HF+	$\mathbf{45.42_{\pm1.01}}$	$\mathbf{80.66_{\pm0.30}}$

HazardFlow also improves frozen backbones without retraining their encoders.



current	t2	t3	t4	t5	t6	t7	t8	t9
PC	-0.21	-0.09	-0.07	-0.17	-0.12	-0.41	-0.35	-0.39

Higher learned hazard consistently corresponds to poorer lactate clearance.

Although the base model misranks Patients 2 and 3, the learned hazard assigns a larger magnitude to the positive Patient 3.

THANK YOU!

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