Intelligent Lung Support for Mechanically Ventilated Patients in the Intensive Care Unit (IntelliLung)

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NIMI NATURE-INSPIRED MACHINE INTELLIGENCE

Introduction

Background: Optimizing mechanical ventilation (MV) is complex and prone to errors. With rising ICU demand and staff shortages by 2030 [3], inappropriate settings risk lung damage and increased mortality.

Objective: Develop AI-based decision support (AI-DSS) system to provide recommendations for MV settings to reduce lung injury and ventilator time.

Significance: The AI system improves ICU care by reducing ventilator time, improving survival, reducing complications, and lowering healthcare costs.

Methods

Data
ICU datasets collected from hospitals across the US and Europe.

ML Evaluation
Using Fitted Q-Evaluation (FQE)[4] to estimate the policy's long-term performance from retrospective data.

Shadow Deployment
The algorithm operates alongside existing systems to safely evaluate its performance in real-world conditions.

Rewards
Designed to promote safe mechanical ventilation practices and minimize ventilator time.

Medical Evaluation
Clinicians review the algorithm's recommendations on offline data systematically.

Target Population
Deployment across hospitals in Germany, Italy, Poland and Spain

Training
Offline RL[1], which learns an optimal policy from retrospective data to improve long-term treatment outcomes.

Bias Detection
Detecting and mitigating biased outcomes across demographic groups.

Explainability
Applying XAI methods, including model-based approaches and SHAP, to explain policy recommendations.

Results

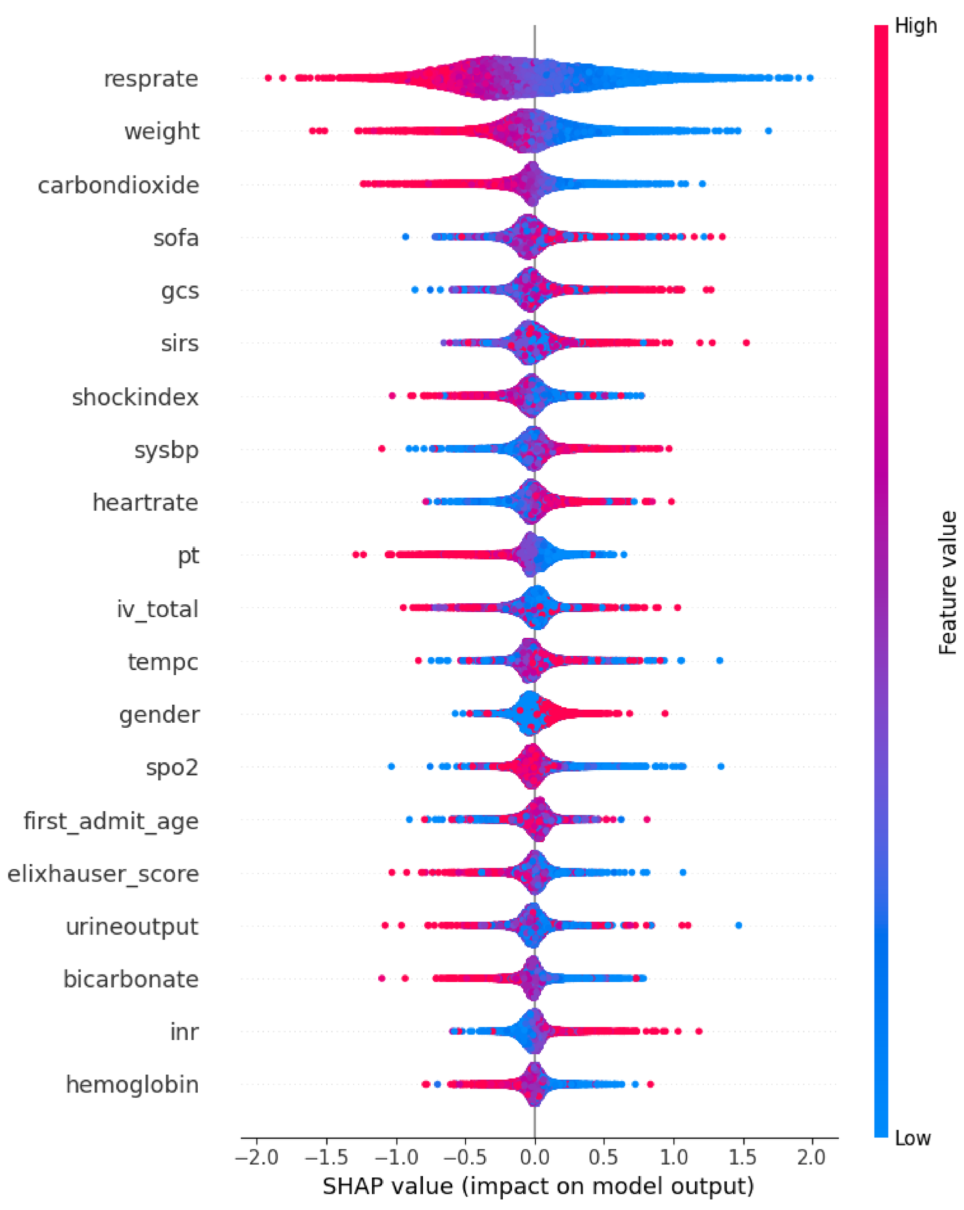

Figure 1: SHAP plot illustrating the influence of features on the policy's choice of ventilation settings [2]

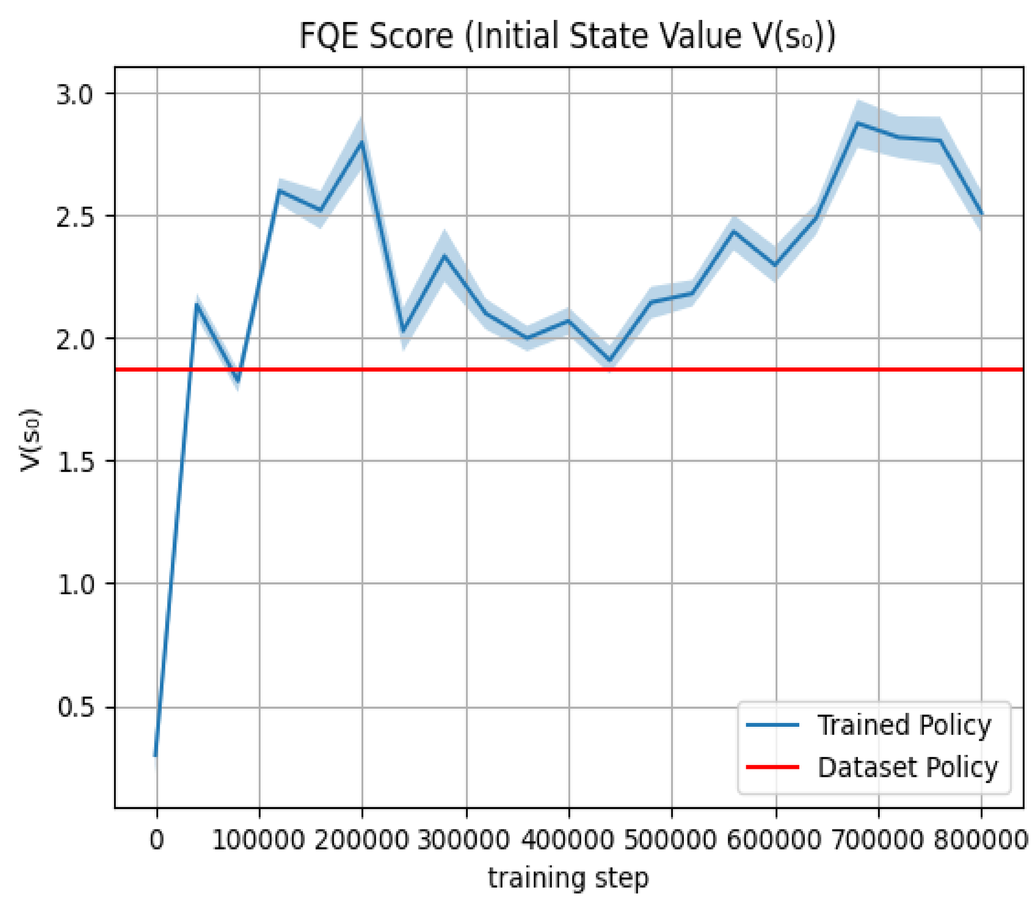

Figure 2: Policy performance over time during training with the Offline RL algorithm.

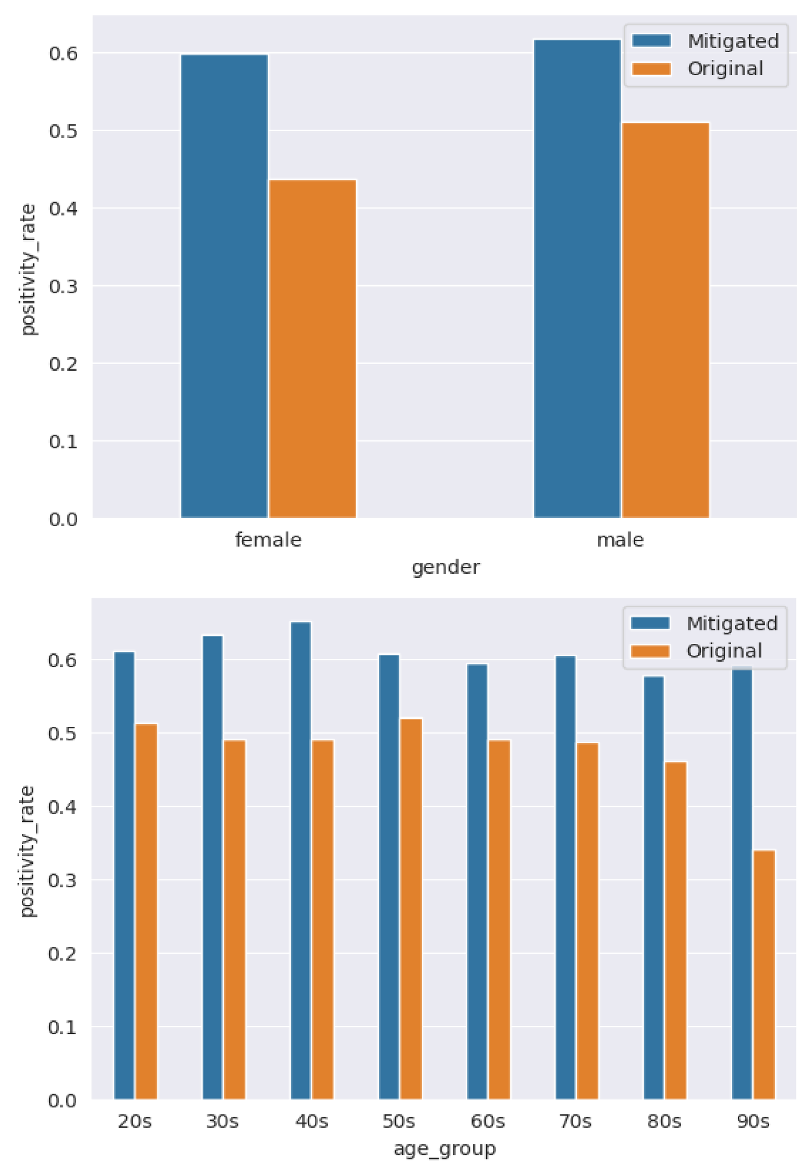

Figure 3&4: Positivity rate depicting the percentage of instances where the algorithm selected higher-performing actions and across different demographic groups (age and gender) before and after applying bias mitigation measures.

Discussion

- The trained policy outperforms clinicians in achieving safer mechanical ventilation and reducing ventilator time (Figure 2).
- It performs similarly or better than clinicians in animal testing.
- Bias mitigation methods improve fairness across different demographic groups (Figures 3 & 4).
- XAI using SHAP values explains the key policy parameters that significantly impact the policy (Figure 1).
- Model-based methods further explain how the current decision will affect future timesteps.

Conclusion

The AI-DSS demonstrates potential in enhancing mechanical ventilation by improving **performance**, treatment **fairness**, and **explainability**.
This project introduces a practical **platform for integrating AI-driven approaches** into clinical settings, serving as a proof of concept for future AI-DSS applications.
Potential directions for **future work** include incorporating multi-modal ICU data, such as textual and visual inputs, to improve state representation. Exploring continuous learning and developing individualized patient policies could further enhance the system's adaptability and impact on patient outcomes.

References

1) Levine, Sergey, et al. "Offline reinforcement learning: Tutorial, review." *and Perspectives on Open Problems* 5 (2020).
2) Safaei, Farhad, et al. "X-Vent: ICU Ventilation with Explainable Model-Based Reinforcement Learning."
3) Karagiannidis, C. "Pneumologie." *Pneumologie*, vol. 73, no. 11, 2019, pp. 670-676, doi:10.1055/a-0976-9119.
4) Le, Hoang, Cameron Voloshin, and Yisong Yue. "Batch policy learning under constraints." *International Conference on Machine Learning*. PMLR, 2019.