A deep-learning algorithm using real-time collected intraoperative vital sign signals for predicting acute kidney injury after major non-cardiac surgeries: A modelling study

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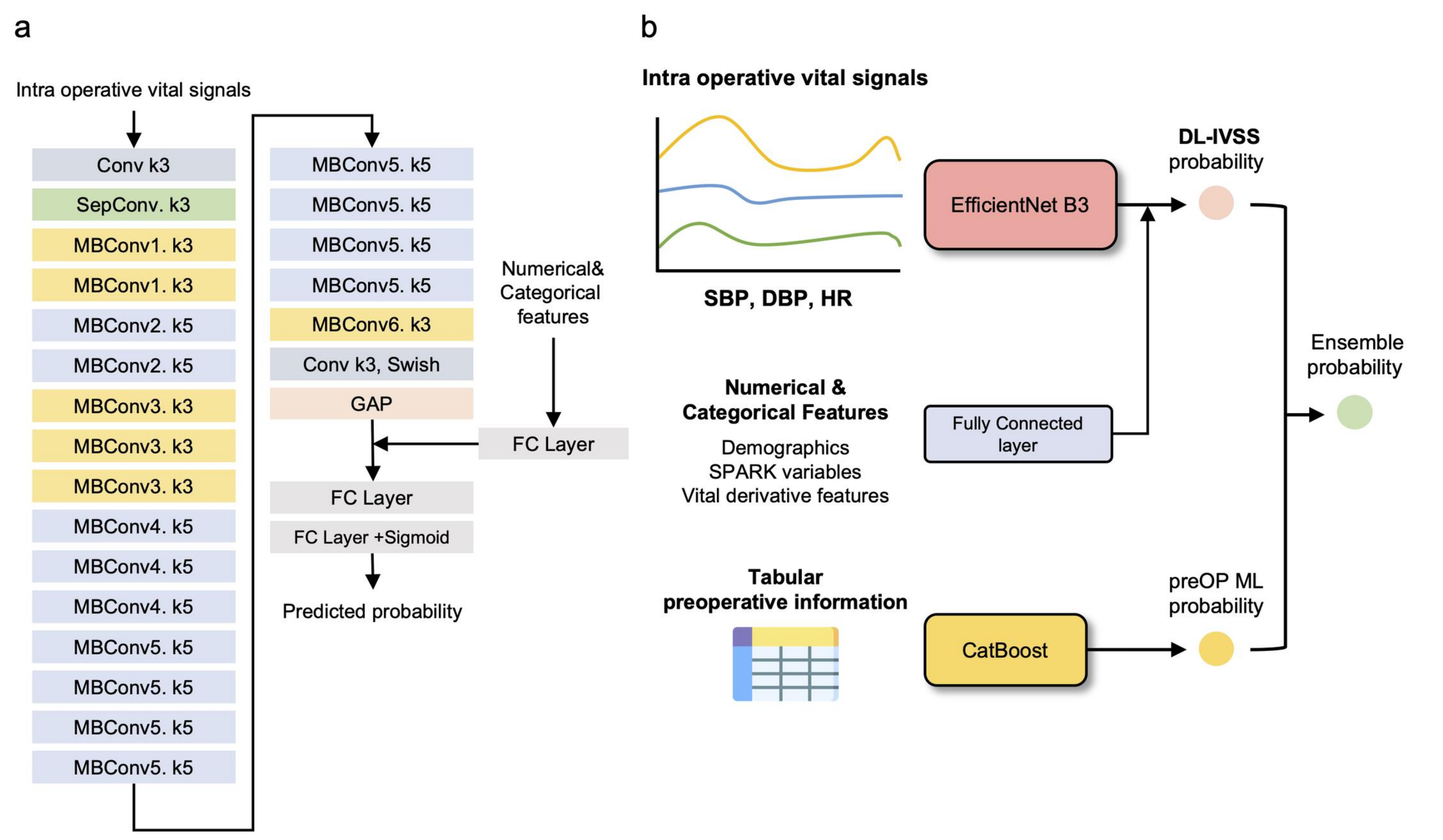
INTRODUCTION

- PO-AKI affects 5-7% of non-cardiac surgeries with high morbidity/mortality [1,2]
- **Current models use only preoperative data (demographics, labs)**, missing critical intraoperative hemodynamics [3,4]
- Kidney susceptibility to BP/HR fluctuations makes **real-time monitoring essential for AKI prediction** [5]
- - Deep learning enables analysis of complex minute-scale vital sign patterns [6]

OBJECTIVES

- Develop a **deep-learning algorithm** using **intraoperative vital sign signals** (DL-IVSS) to predict PO-AKI
- Compare **DL-IVSS** with traditional preoperative-only models
- Evaluate **Ensemble approach** combining clinical variables with DL-IVSS
- **External validation** across multiple hospital cohorts

METHODS



• **Study Design**: **Multi-center retrospective cohort (n=110,696)**
- Developmental: Seoul National University Hospital (SNUH) (n=51,345)
- External Validation 1: SNUH Bundang Hospital (SNUBH) (n=47,093)
- External Validation 2: SNU Boramae Medical Center (SNU-BMC) (n=12,258)

• **Data Collection**
- **Minute-by-minute vital signs**: systolic/diastolic BP, heart rate (~9.3 million data points)
- **Preoperative clinical variables**: demographics, comorbidities, lab values

• **Model Architecture**
- **CNN-based EfficientNet B3** for time-series vital sign processing
- **Ensemble model** combining CNN with CatBoost for tabular data

•**Outcome**: **PO-AKI** by KDIGO criteria **within 7 days post-surgery**

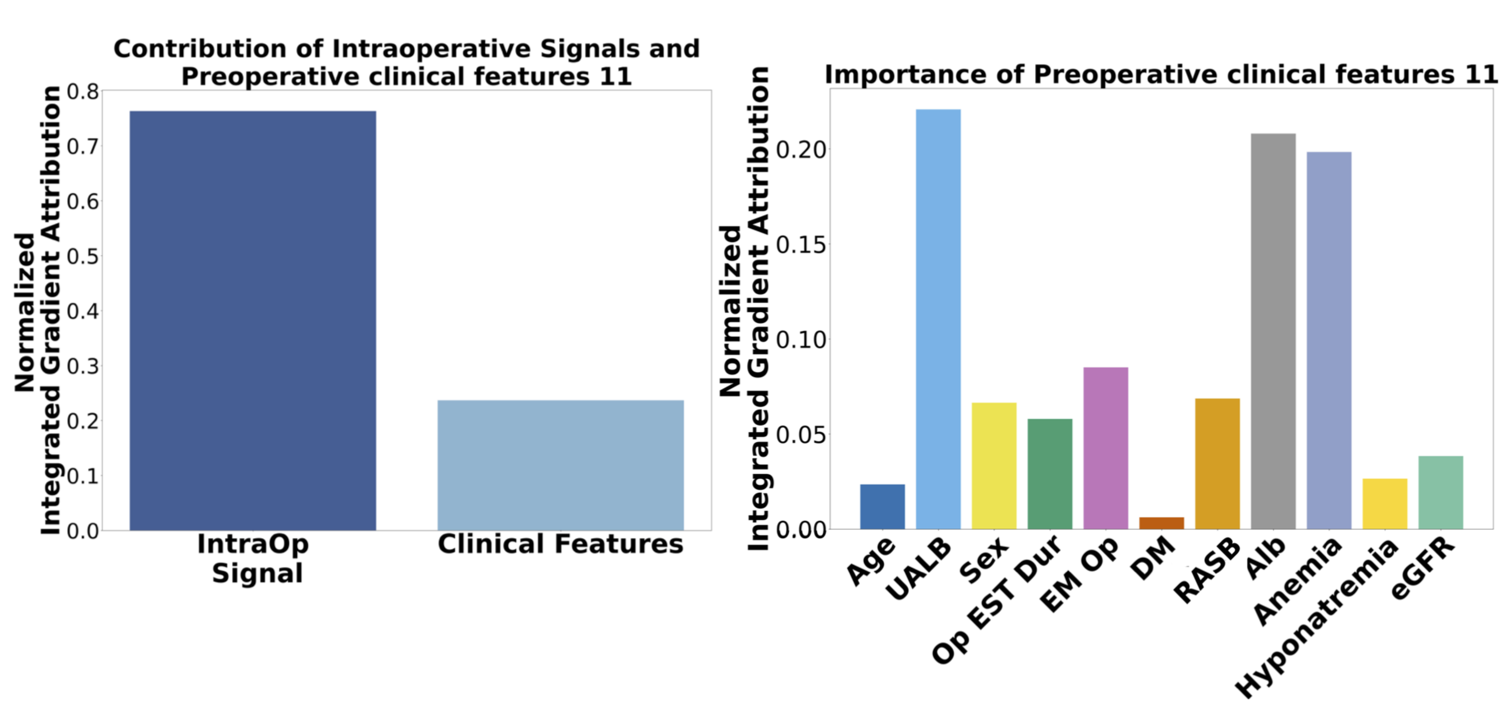
RESULTS

Performance Comparison

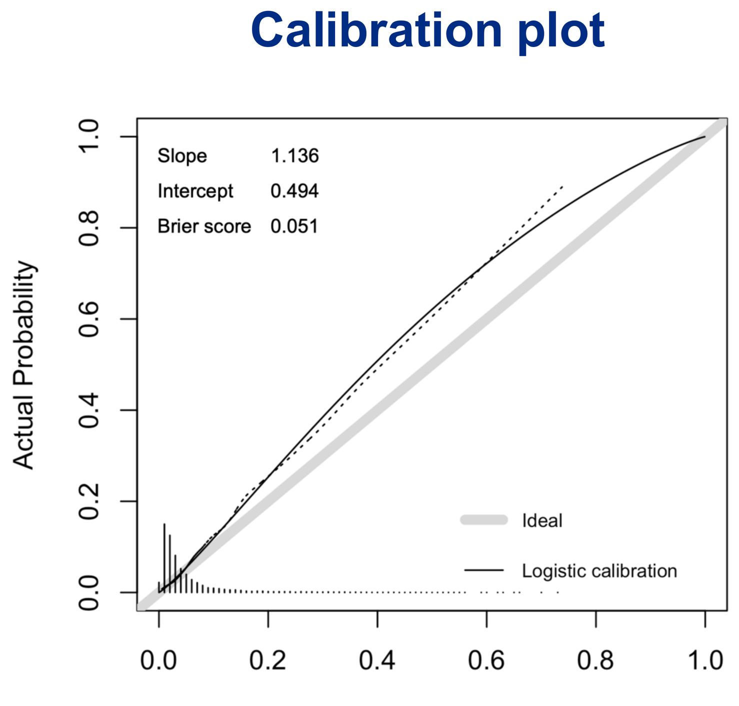
Hospital (Cases N (%))	Method	AUROC	Balanced Accuracy
Developmental cohort (3,188 (6.2%))	SPARK	0.724	0.664
	DL-IVSS_only	0.707	0.666
	DL-IVSS_PCFs 11	0.765	0.708
	Ensemble_PCFs 11	**0.795**	**0.732**
EVC 1 (2,519 (5.3%))	SPARK	0.697	0.646
	DL-IVSS_only	0.637	0.601
	DL-IVSS_PCFs 11	0.716	0.655
	Ensemble_PCFs 11	**0.762**	**0.696**
EVC 2 (579 (4.7%))	SPARK	0.745	0.689
	DL-IVSS_only	0.607	0.588
	DL-IVSS_PCFs 11	0.761	0.701
	Ensemble_PCFs 11	**0.786**	**0.715**

DL-IVSS_only; only use Intra operative signals
DL-IVSS_PCFs 11; add Preoperative Clinical Features 11 on DL-IVSS_only
Ensemble_PCFs 11; CatBoost + DL-IVSS_PCFs 11

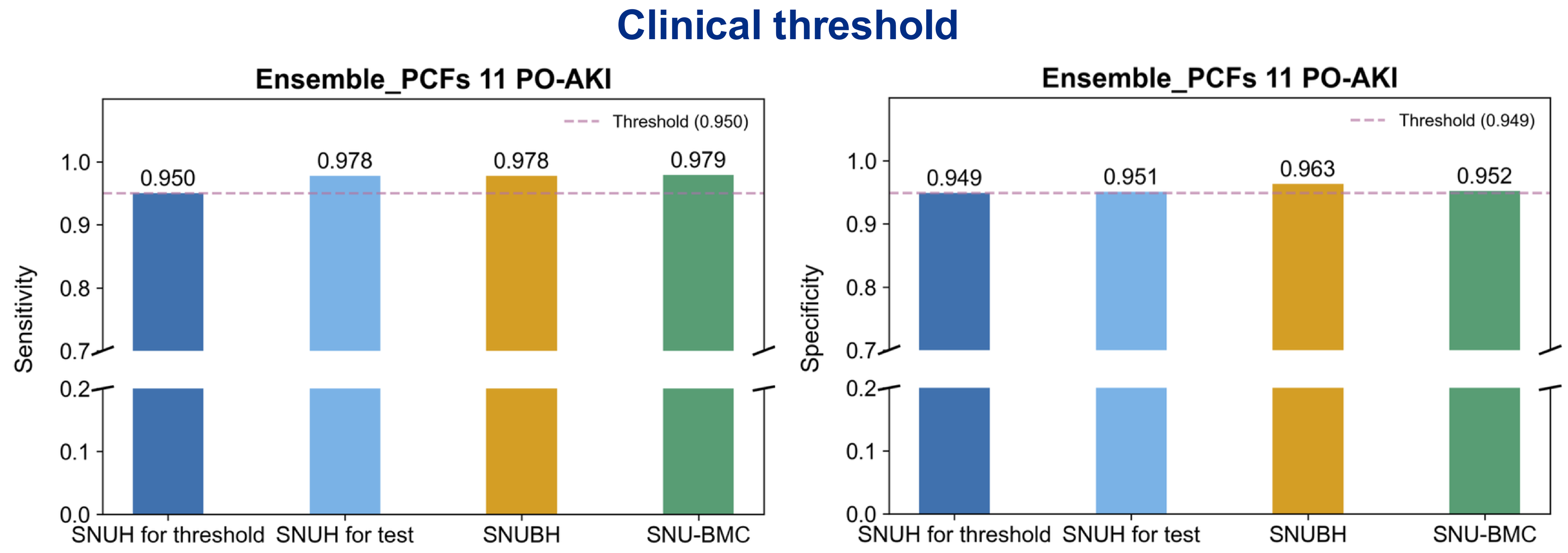
Feature importance



Calibration plot



Clinical threshold



CONCLUSION

- **First study** to leverage **minute-scale intraoperative vital signs** (~9.3M data points) for PO-AKI prediction
- **Ensemble model achieved superior performance** (AUROC 0.795) vs. conventional SPARK model (0.724)
- **Intraoperative hemodynamics outperformed preoperative factors** in feature importance analysis
- **Clinical utility**: Model maintains **>95% sensitivity and >95% specificity** at preset thresholds across validation cohorts
- **Robust external validation**: Consistent performance across 3 independent hospital datasets

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