Making improved predictions of Non-invasive Continuous Arterial Blood Pressure through leveraging EHR medication data

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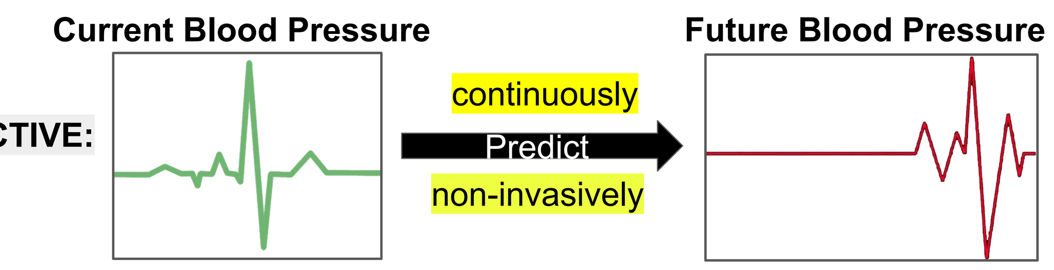
Introduction & Background

Hypotension (a sustained decrease in blood pressure) within critical care patients is associated with a higher risk of mortality and other severe complications. It is periodically monitored non-invasively for all ICU patients. Continuous blood pressure monitoring via arterial line catheters has been shown to lead to faster response times but is also associated with complications such as infection. With recent advances in machine learning, we take an innovative approach and train a model that is able to predict Arterial Blood Pressure continuously and non-invasively through the following three measures: Electrocardiogram, Photoplethysmography, and EHR Vasopressors medication.

OBJECTIVE:

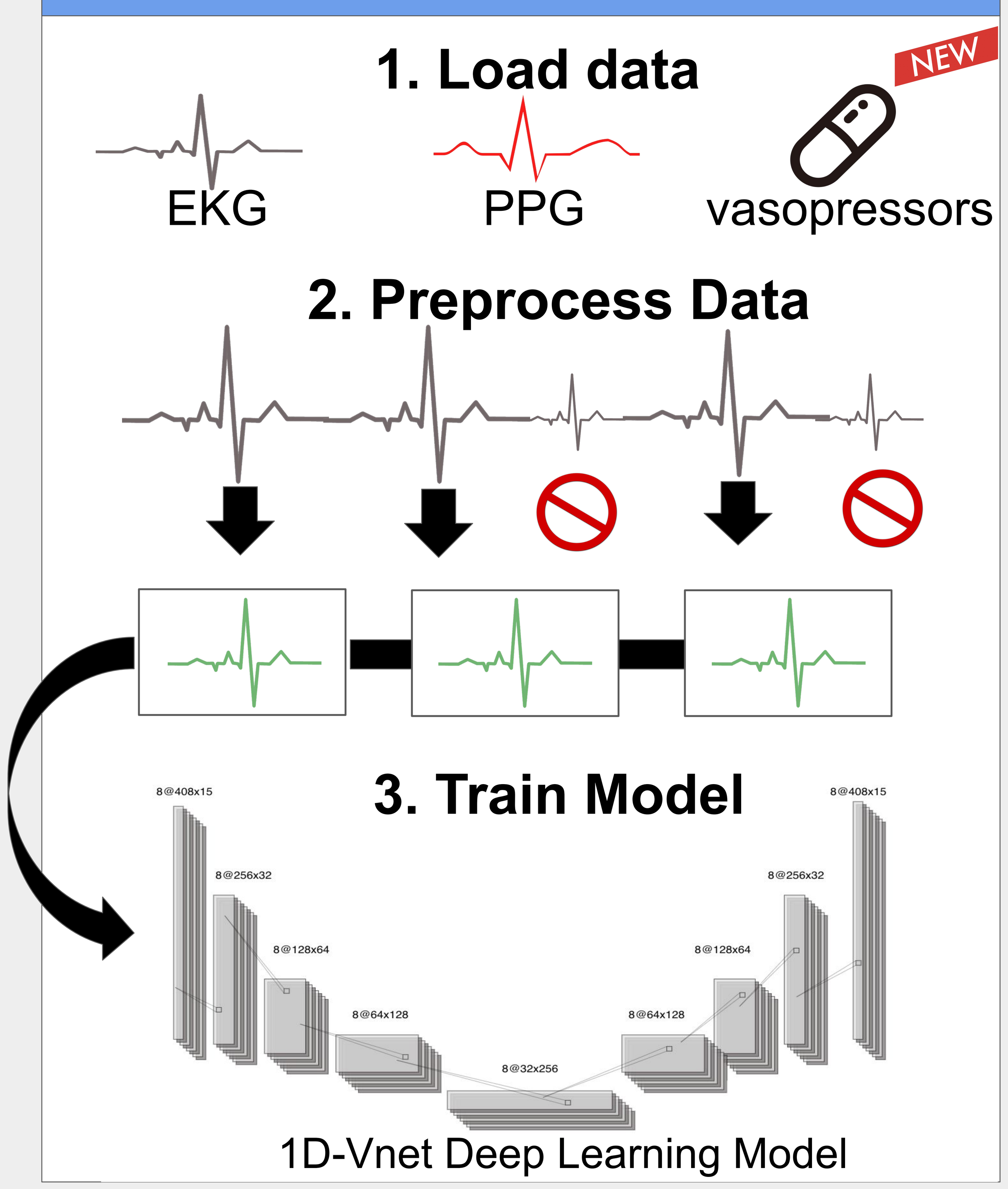


MIMIC-III Data

MIMIC MIMIC-III is a large, freely-available database comprising deidentified health-related data associated with over 40,000 patients who stayed in critical care units.

	Training	Testing
Patient Samples	18	2
Frames (400 msec)	218,649	24,295
BP mean (mmHg)	72.9	73.7
Data Size (Gb)	129.70	14.41

Methods



Results

Figure 1

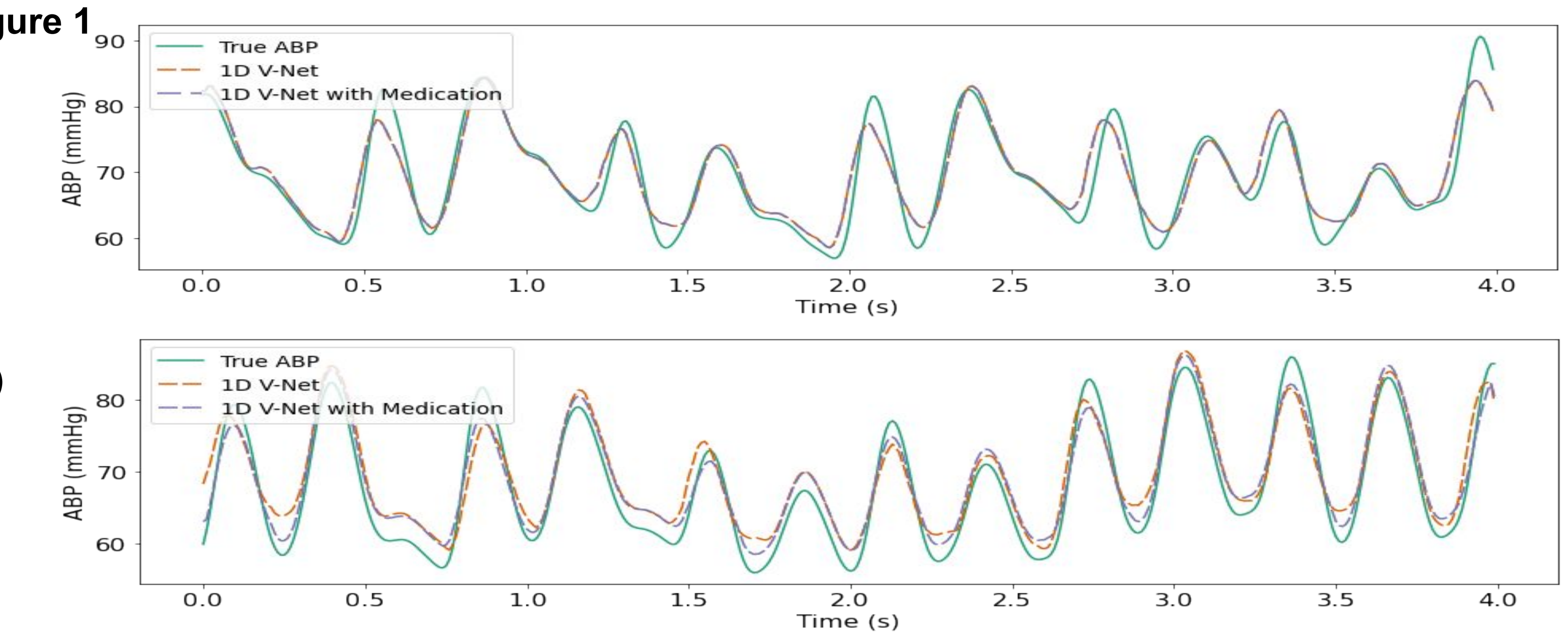
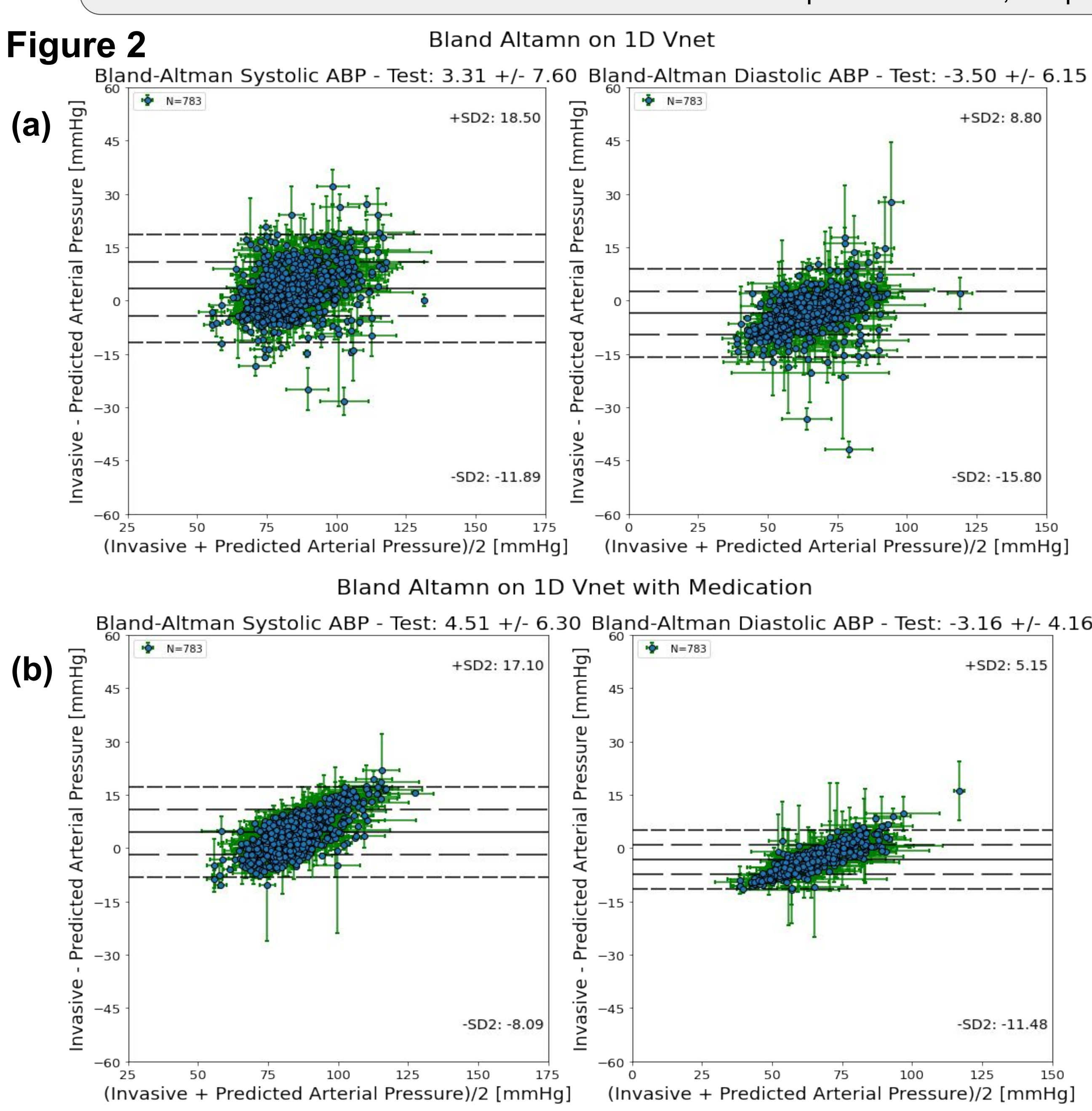


Fig. 1a Displays a predicted waveform with a patient with no vasopressor medication administered. By no surprise, we see that the predictions are identical. In **Fig. 1b**, we see differentiation between the first model versus our current model which takes into account clinical interventions. In this particular frame, the prediction is performing better than the original.

Figure 2



- Bland–Altman plots for the MIMIC ICU test cohorts. Systolic BP measurements per patient (left), and Diastolic BP measurements per patient (right) using a four second window.
- In **Fig. 2a,** we see the Bland-Altman of our original model which has a Systolic ABP mean of 3.31 +/- 7.60 standard deviations and a Diastolic ABP mean of -3.50 +/- 6.15 standard deviations.
- In **Fig. 2b,** we notice that the mean of the Systolic ABP is slightly larger at 4.31 but has a smaller standard deviation. We also notice that the Diastolic ABP outperforms the original model in both its average and standard deviation.
- Although our mean average is slightly larger in our newer model by 0.43, we see that our new model has data that is more mean centered with its smaller standard deviation. Future work is needed to determine if this pattern holds beyond our two test patients.

Discussion & Conclusion

	ABP Imputer	ABP Imputer w/ med
$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Predicted_i - Actual_i)^2}{N}}$	6.106 (5.855-6.356)	5.665 (5.259-6.085)
Correlation $r = \frac{\Sigma(x-\bar{x})(y-\bar{y})}{\sqrt{[\Sigma(x-\bar{x})^2(y-\bar{y})^2]}}$	0.860	0.904

- We see a slight improvement in diastolic prediction performance and a slight worsening in systolic performance.
- As briefly mentioned in the results section, our mean is highly representative and that there are less poorly predicted waveforms
- We have presented a novel method for imputing the arterial blood pressure waveform that is continuous, non-invasive, accurate, for patients in the ICU setting and beyond, without the need for any additional instrumentation.

Future Works

- Optimize and scale the approach up to massive datasets.
- Test on additional datasets collected from different patient populations.
- Explore optimal approaches of representing clinical interventions.

References & Code

1. Hill, B.L., Rakocz, N., Rudas, Á. *et al.* Imputation of the continuous arterial line blood pressure waveform from non-invasive measurements using deep learning. *Sci Rep* 11, 15755 (2021). https://doi.org/10.1038/s41598-021-94913-y

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