# Machine Learning for Automated Bladder Event Classification from Single-Channel Vesical Pressure Recordings

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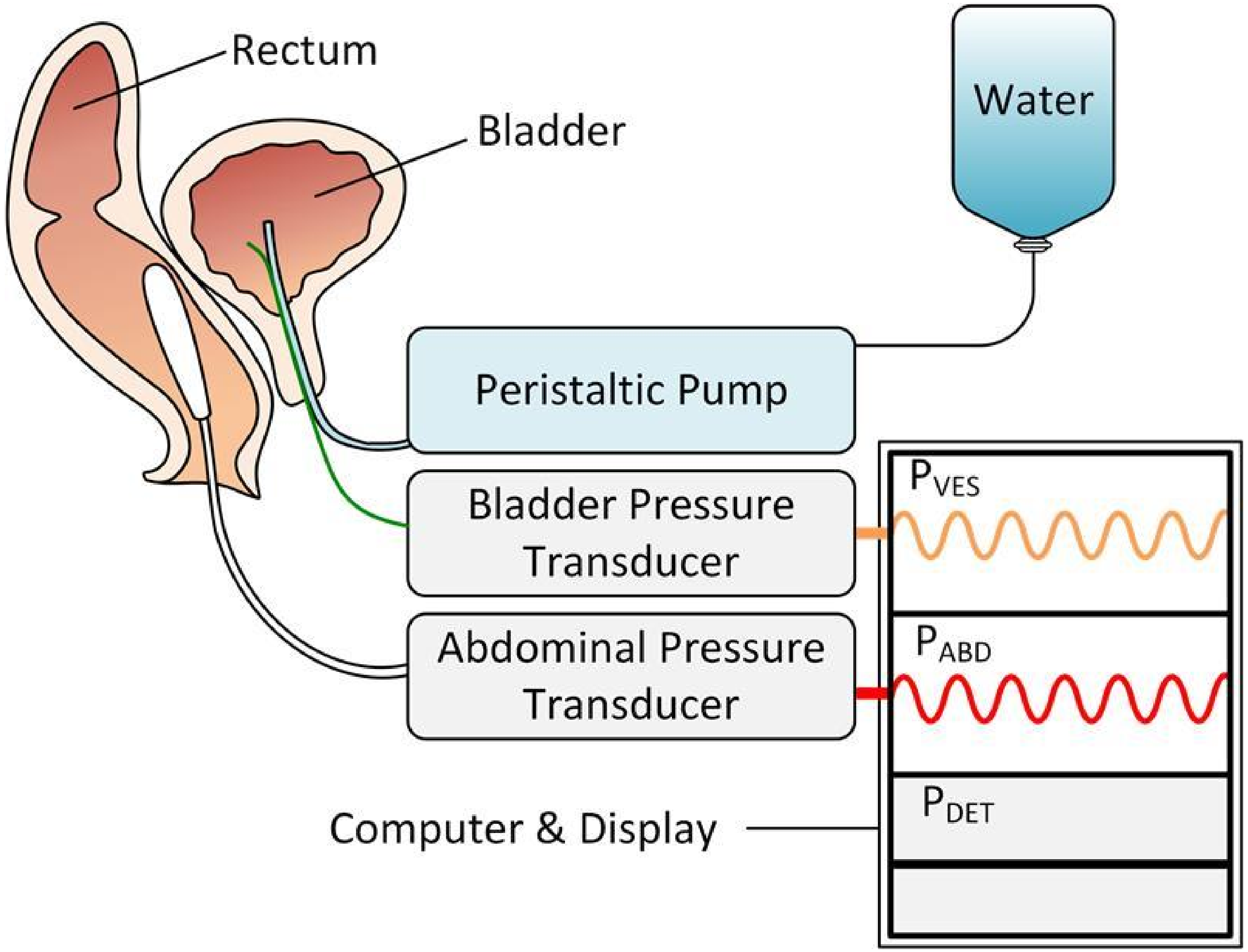
# Introduction

- Urodynamics (UDS): assessment of urinary tract function
    - Diagnosis of urinary incontinence, detrusor overactivity
- Bladder contraction: emptying (voiding) of bladder
- Detrusor overactivity (DO): involuntary bladder contractions

    → Increased frequency of urinary urges

# Introduction

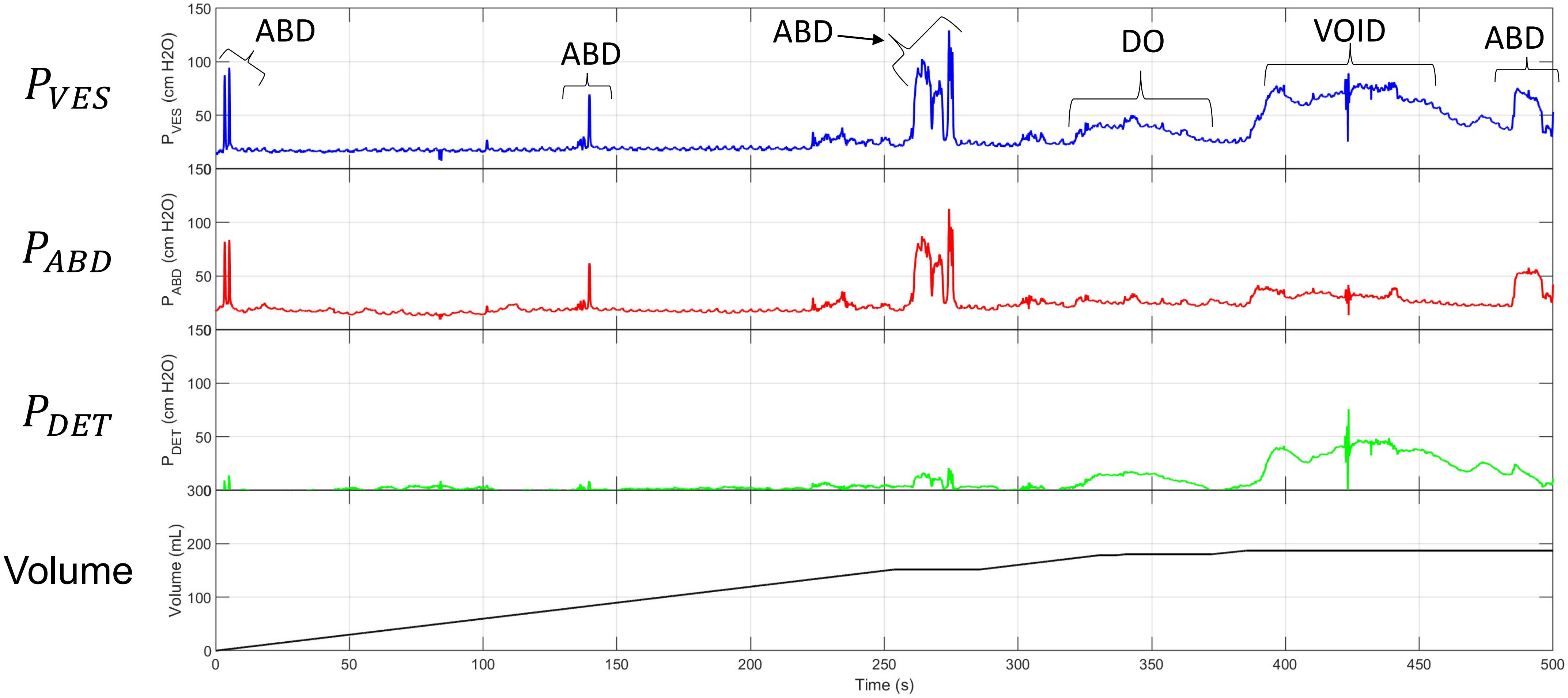



$$P_{DET} = P_{VES} - P_{ABD}$$

- UDS: simulate filling and voiding of bladder
- Typically requires insertion of **two** catheters
  → Source of discomfort

# Introduction

- ABD → abdominal event (cough, Valsalva)
- DO → detrusor overactivity (involuntary contraction)
- VOID → voiding (voluntary contraction)

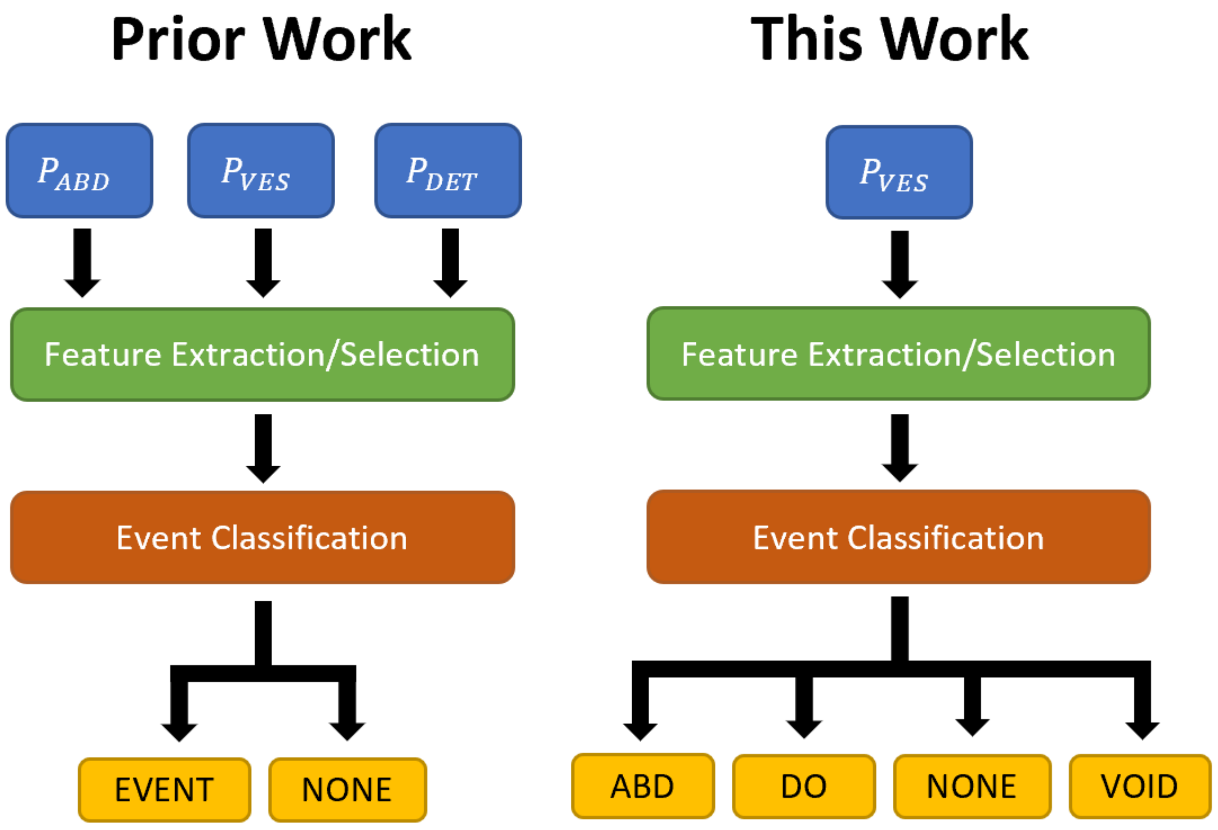


# Introduction

- Interpretation of UDS traces: **subjective** and **variable**
- Need a standardized, **automated** methodology for UDS annotation/interpretation from **single-catheter data**

# Introduction

- Prior work
  - Multiple pressure channels
  - Single event classification
- Our work
  - **Single-channel data ($P_{VES}$)**
  - **Multi-event classification**
  - **Supervised machine learning**



# Methodology

- ABD → abdominal event (cough, Valsalva)
- DO → detrusor overactivity (involuntary contraction)
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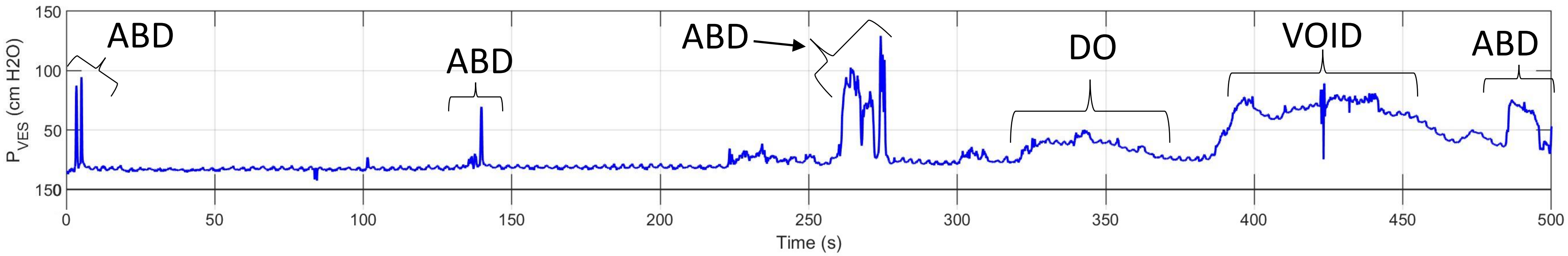



- Isolated $P_{VES}$
- Goal: reproduce annotations from this **single channel** of data using **supervised machine learning**

# Methodology

## Dataset Preparation

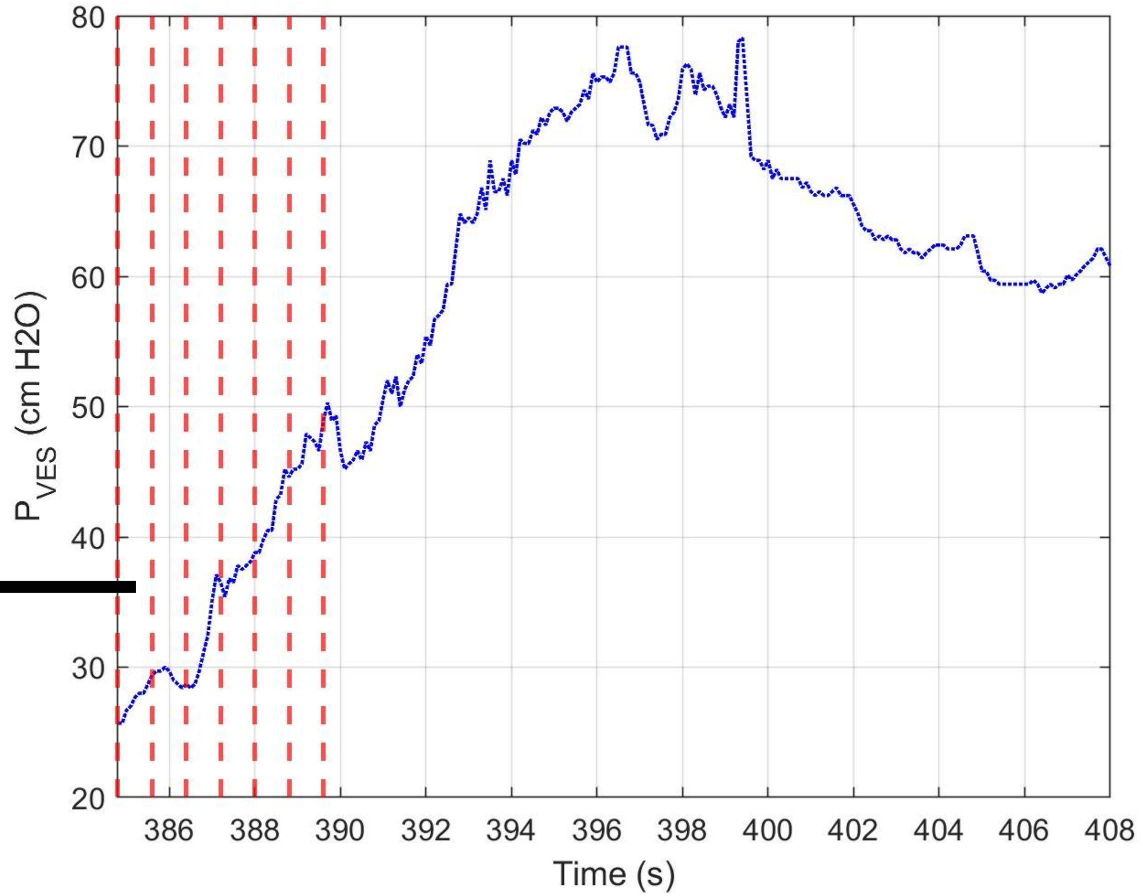
- Anonymized data obtained from previous studies
  - Louis Stokes Cleveland VA Medical Center and Cleveland Clinic
- 60 UDS tracings sampled at 10 Hz
  - From 34 human subjects with overactive bladder or neurogenic urinary incontinence
- Noisy segments discarded
- Annotated with assistance of urologist

# Methodology

## Data Segmentation

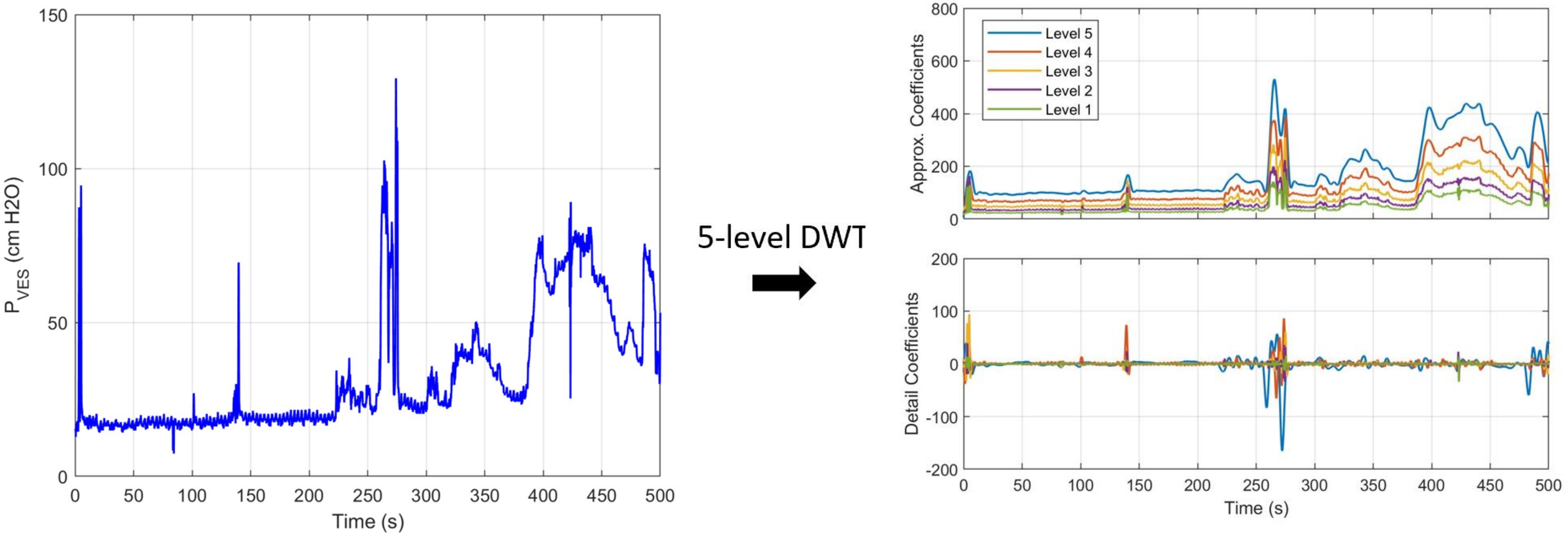
- $P_{VES}$ segmented into 0.8-second intervals
  - Increased range of values for deriving more statistical features
  - Maintained time precision; relevant for real-time inference

Label $P_{VES}$ interval based on presence of event: ABD, DO, NONE or VOID



# Methodology

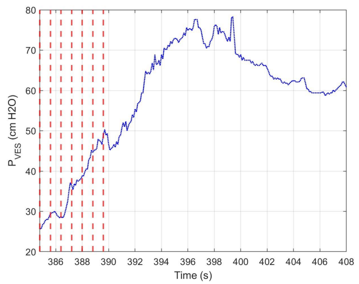
## Wavelet-Based Feature Extraction




- Discrete wavelet transform (DWT) using Daubechies 4 wavelet
  - Allows for time-frequency localization in non-stationary signals

# Methodology

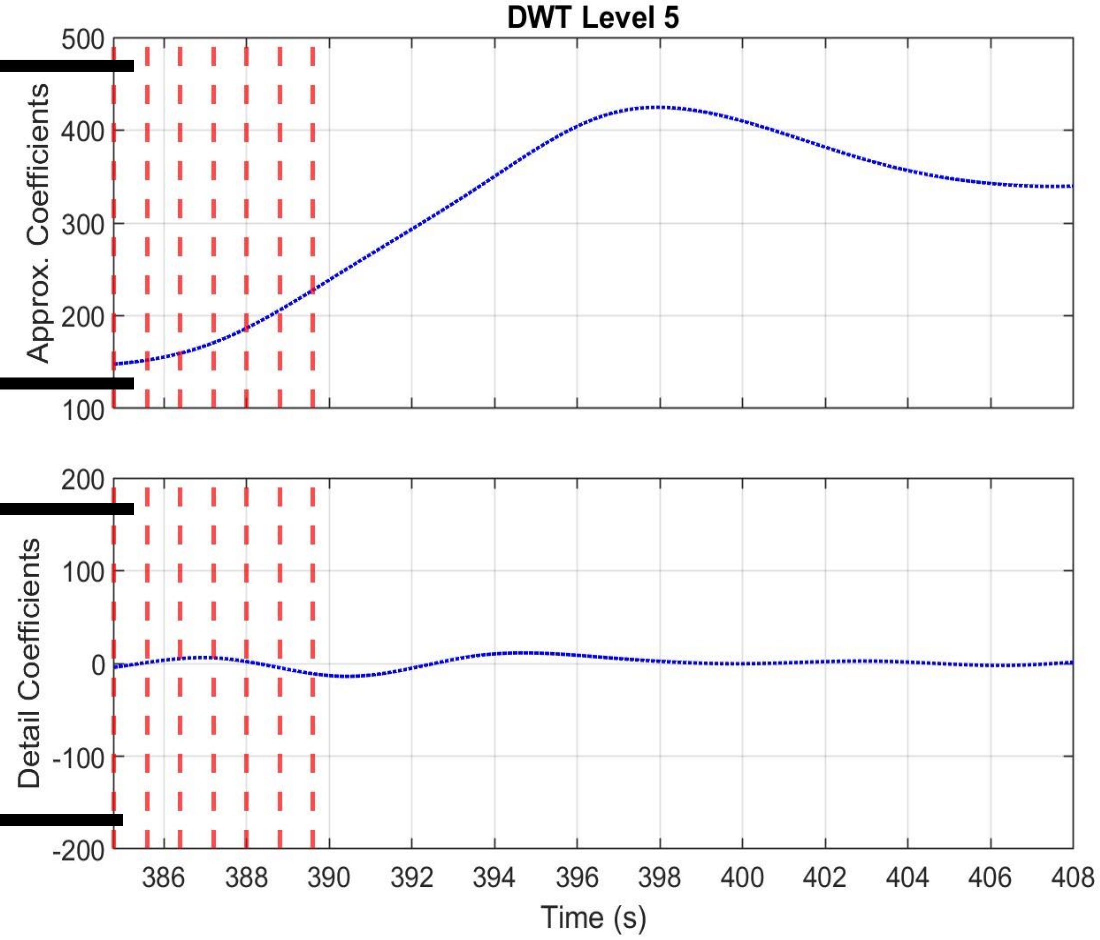
## Wavelet-Based Feature Extraction




Compute **max, MAV, median, Shannon entropy** from approx. coefficient segment

Compute **max, mean, median** from cross-correlation segment between approx./detail coefficients

Compute **max, MAV, median, Shannon entropy** from detail. coefficient segment



# Methodology

## Dimensionality Reduction through Feature Selection

- Total number of features: 55
  - Based off wavelet-based feature extraction for common bio-signal classification tasks (ECG, EEG, EMG)
- Relief-F method: identified $m$ most relevant features
  - K-nearest neighbors approach
  - $m$ varied for each classifier architecture

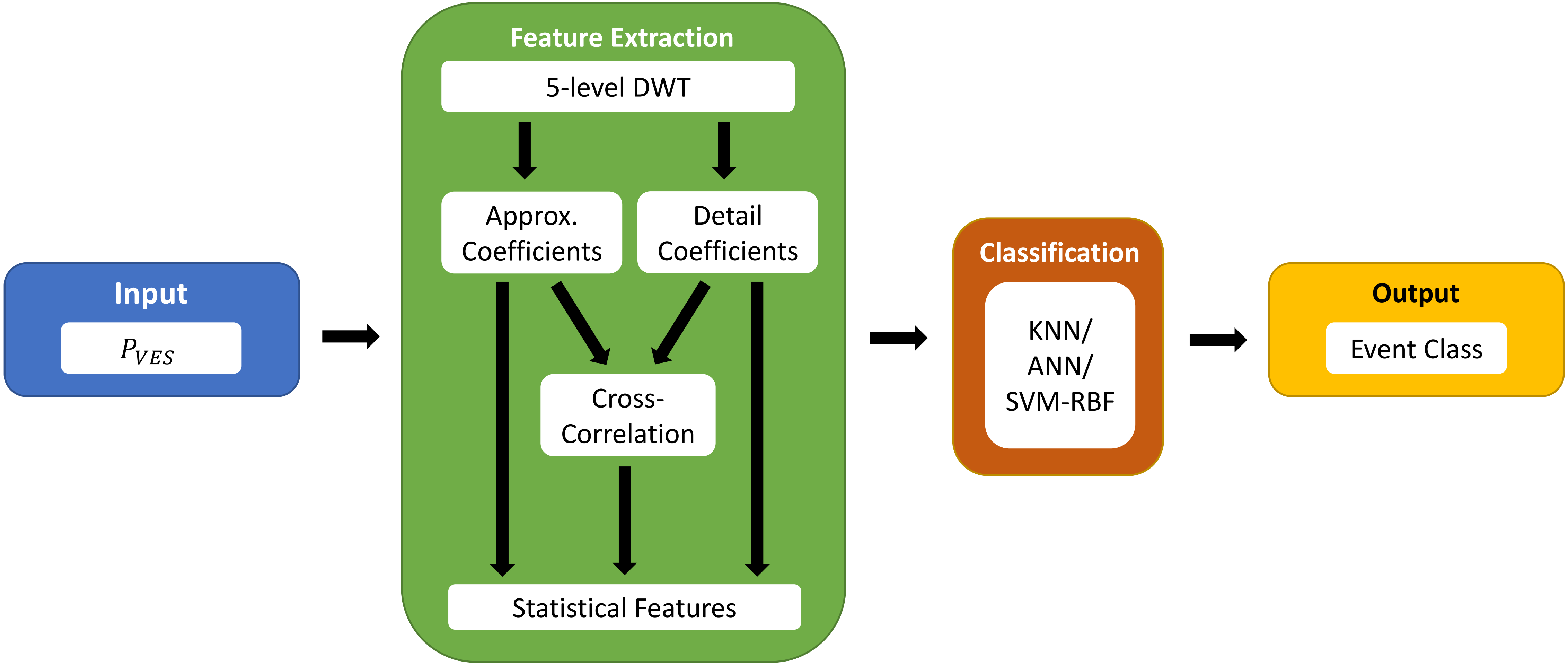
# Methodology

## Classifier Selection

| Classifier | Hyperparameters | Number of Features |
|---|---|---|
| $k$-Nearest Neighbors (KNN) | $k = 1$ | 12 |
| Artificial Neural Network (ANN) | Hidden layers: 2 x 100 neurons/layer<br>Activation: ReLU | 55 |
| Support Vector Machine (SVM) | Kernel: Radial Basis Function (RBF)<br>$\gamma = 0.94$ | 12 |

# Methodology

## Full Algorithm



# Methodology

## Test Procedure & Performance Metrics

- Dataset: **7,861** 0.8-second events
  - Balanced between all four classes
- Performed five-fold cross-validation

$$Sensitivity\ (Recall) = \frac{TN}{TP + FP}$$

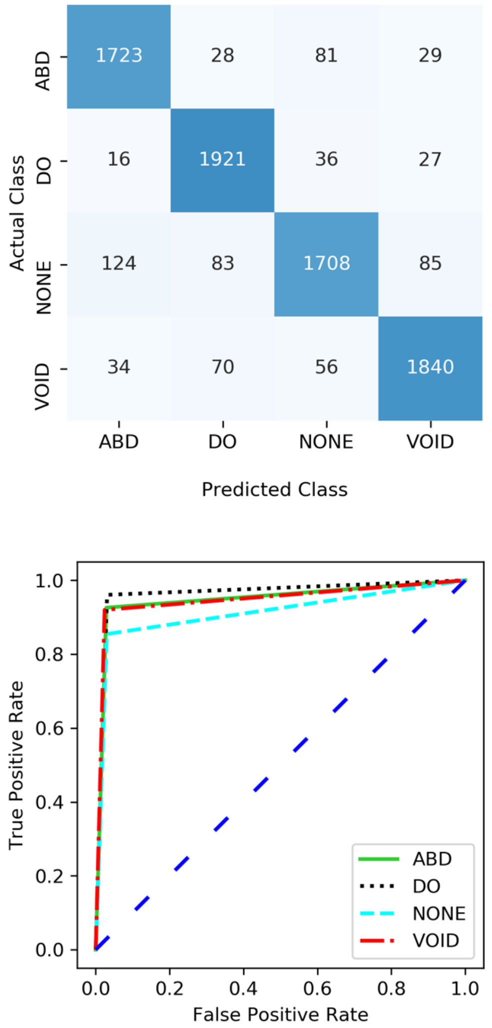
$$Specificity = \frac{TN}{TN + FP}$$

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

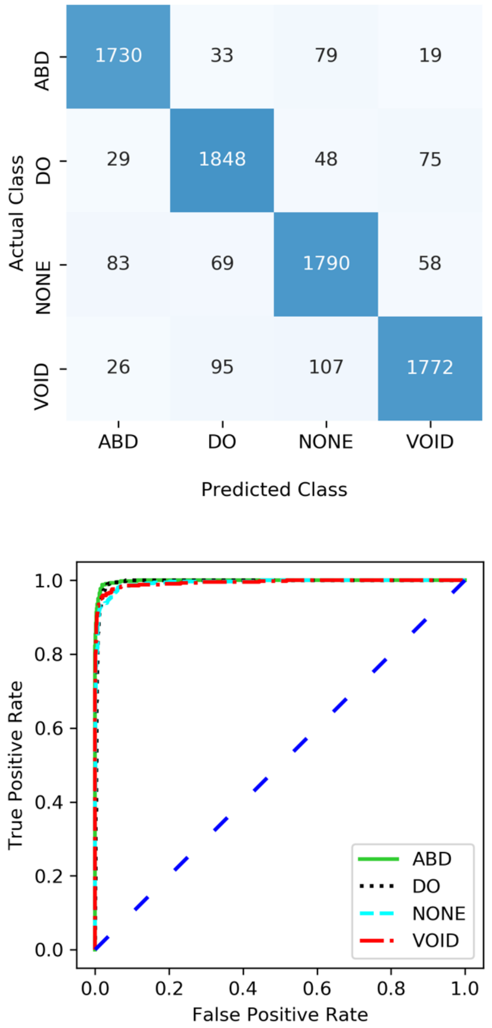
$$F1 = \frac{2 \times (Precision \times Recall)}{Precision + Recall}$$

# Results and Discussion

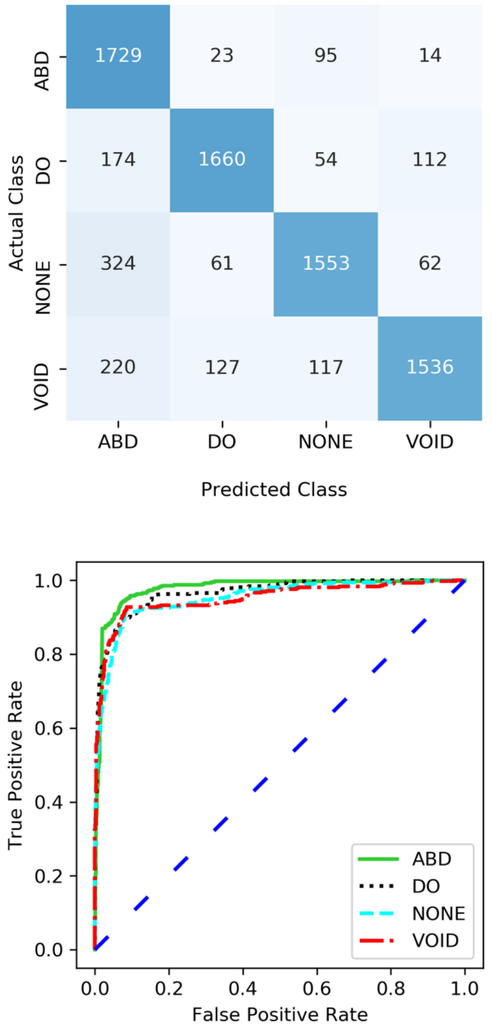
## KNN




## ANN




## SVM-RBF



# Results and Discussion

| Classifier | Accuracy |
|---|---|
| KNN | 91.49% |
| ANN | 90.83% |
| SVM-RBF | 82.41% |

- KNN: high sensitivity to “DO” and “VOID”
  → Most successful with these events
- ANN classifier: most effectively generalized to all four classes
  - More balanced sensitivity scores
  - Highest ROC AUC’s for all four classes
- Future work
  - Take advantage of memory: RNN/LSTM
  - Real-time hardware implementation of neural network approach

# Results and Discussion

SUMMARY OF RELATED WORKS

| Work | Year | Channels | Feature Extraction | Classification | Classes | Findings |
|---|---|---|---|---|---|---|
| R. Karam et al. [7] | 2016 | 1 | 5-level DWT | Adaptive thresholding | 2 | 97% true positive rate |
| H.-H. S. Wang et al. [5] | 2020 | 3 | Wave-shape manifold model | Dynamic time warping | 2 | 81.35% accuracy, 0.84 ROC AUC |
| K.T. Hobbs et al. [6] | 2021 | 3 | Windowed time/freq. analysis | SVM-RBF | 2 | 0.91 ROC AUC |
| Proposed | 2022 | 1 | 5-level DWT | KNN, ANN, SVM-RBF | 4 | 91.49%, 90.83%, 82.41% accuracies, ROC AUCs ranging 0.91-0.99 |

# Conclusion

- First supervised machine learning framework for classifying **multiple bladder events**
- Three classifiers with accuracy ranging from ~82% to ~91%
- Demonstrated efficacy of this approach using **single-channel vesical pressure data**
- Can aid in automated UDS interpretation while reducing number of catheters

# Questions?

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