Automatic Classification of Audio Uroflowmetry with a Smartwatch

G. NARAYANSWAMY [1], L. ARJONA [2], L.E. Díez [2], A. Bahillo [2], S.N. Patel [1]
1 University of Washington, Seattle WA, USA
2 University of Deusto, Bilbao, Spain

INTRODUCTION

Prior work has shown the classification of voiding (urine flow) dysfunctions from uroflowmeter data using machine learning [1]. We present the use of **smartwatch audio**, collected through the UroSound platform, in order to **automatically classify voiding signals** as normal or abnormal, using classical machine learning techniques. We train several classification models using classical machine learning and report a **maximal test accuracy of 86.16%** using an ensemble method classifier.

This classification task has the potential to be part of an essential toolkit for urology telemedicine. It is especially useful in areas that lack proper medical infrastructure but still host ubiquitous audio capture devices such as smartphones and smartwatches.

DATASET

- **Data Collection System:** UroSound platform [2] and Oppo Smartwatch
- **Clinical Data Collection:** Voiding signals from 14 volunteer patients across two pelvic floor health clinics in Spain
- **Data Distribution:** 30% abnormal flows (#1), 70% normal flows (#0). Total to of 153 audios
- **Data Augmentation:** Each audio augmented in 3 ways (-5dB gain, +5dB gain, added 5dB Gaussian noise). Total of 612 audios

User	Trials	# 0	# 1	User	Trials	# 0	# 1
A2	12	9	3	**B5**	12	7	5
A3	14	5	9	**B7**	14	9	5
A4	15	8	7	**B8**	7	3	4
A5	9	8	1	**B9**	8	4	4
A6	12	12	0	**B10**	3	2	1
A7	15	11	4	**B11**	9	9	0
B3	16	12	4	**B12**	7	7	0

Table 1: Dataset audios by clinical participant

METHODS

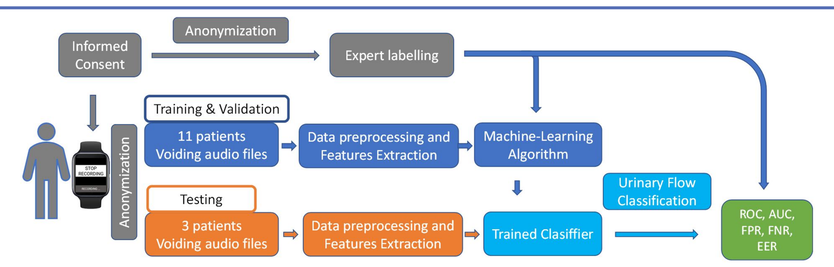

Fig. 1: Voiding classification pipeline

Data Preprocessing

This process is visualized in **Figure 2**.

1. **Raw Audio:** voiding signal read in
2. **Lowpass Filter:** LPF to remove high frequency noise
3. **Hampel Filter:** Outlier replacement
4. **Envelope Extraction:** Hilbert-based envelope extraction
5. **Moving Median Smoothing:** Envelope smoothing

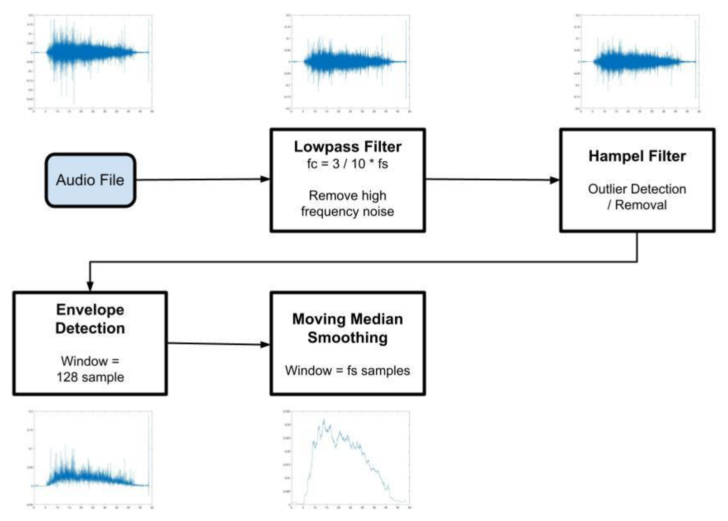

Fig. 2: Audio signal processing pipeline

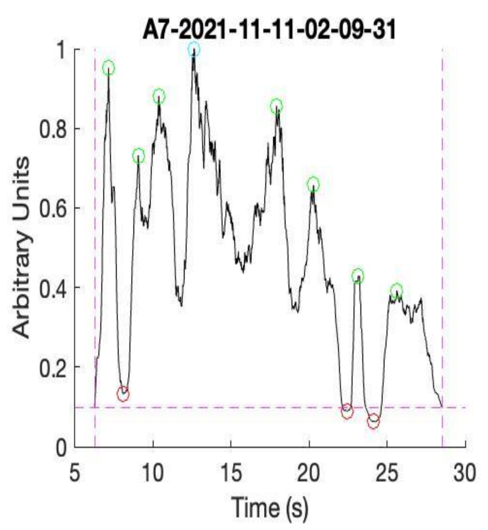

Fig. 3: Example envelope features

Feature Selection and Extraction

- Timing and flow parameters derived from signal envelope and used for model training and evaluation
- Features adapted from [1] described in **Table 2**

Feature	Description
Voiding Time	Duration of voiding flow
Time to Max. Flow	Time to peak of flow signal envelope
Max. Flow Rate	Peak value of flow signal envelope
Avg. Flow Rate	Average value of flow signal envelope
Interruptions	# of occurrences of flow falling below background noise or 20% of max flow
Fluctuations	# of occurrences of flow peaking with prominence of at least 20% of max flow
Background Noise	Averaged first and last second of signal envelope

Table 2: Model features

Model Selection and Training

3-fold cross-validation with 3 participants held out for test

- **Ensemble Method:** As described by LogitBoost algorithm [3]
- **Random Forest:** 250 trees as described by Breiman's random forest [4]
- **Regression Forest**: 250 trees using all 7 features for splits

RESULTS

Model	FPR	TPR	EER	AUC	ACC
Ensemble Method	6.67%	67.86%	**21.21%**	**0.8919**	**86.16%**
Random Forest	**3.34%**	55.56%	22.24%	0.8754	85.62%
Regression Forest	9.12%	**68.10%**	23.12%	0.8476	84.03%

Table 3: Model Comparison

- Ensemble models perform well on uroflowmetry data. This is consistent for audio uroflowmetry as well
- Ensemble method model achieves a classification accuracy of **86.16%** on voiding signals from individuals not found in the training set

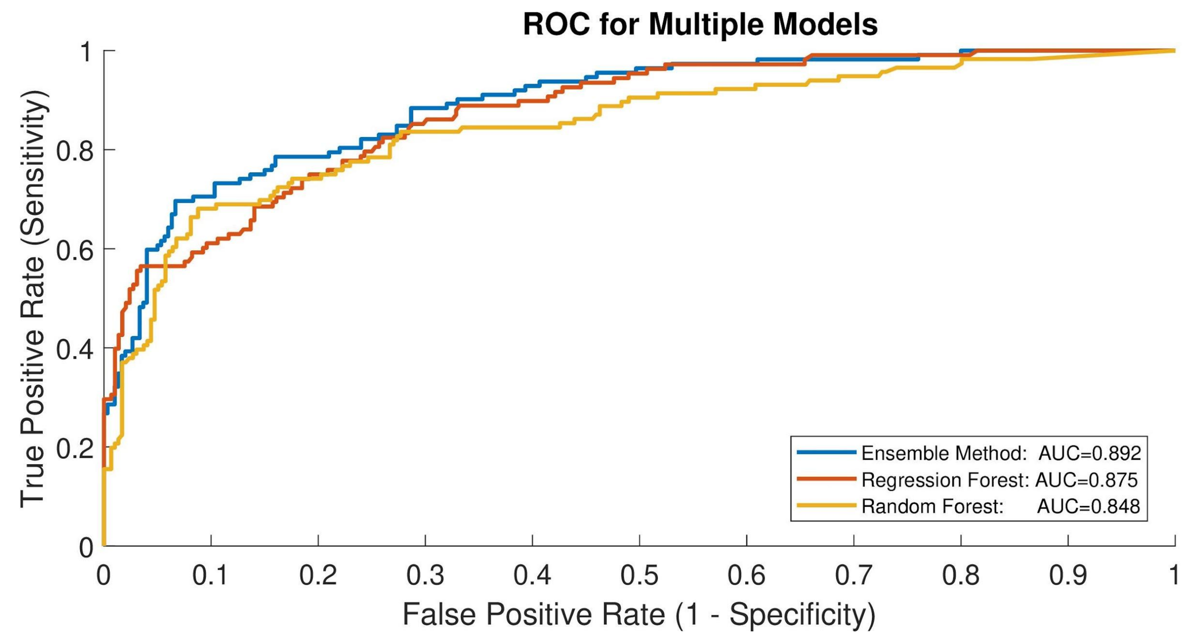

Fig. 4: Voiding envelope features

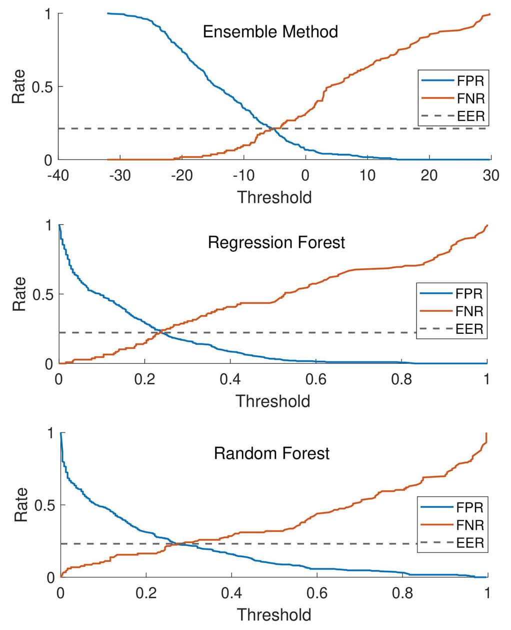

Fig. 5: Voiding envelope features

CONCLUSIONS

We present the use of classical machine learning to classify voiding audio signals, recorded with a commodity smartwatch, as either normal or abnormal. Using 3-fold cross validation we explore a number of ensemble models and achieve a classification accuracy of **86.16%** and an equal error rate of **21.21%**. using an Ensemble Method classifier.

Future research in the area includes continued clinical data collection, deep-learning based classification of voiding pathologies, and automatic voiding-signal detection.

REFERENCES

[1] S. Baas, "A machine learning approach to the automatic classification of female uroflowmetry measurements," 2016.

[2] 2021. [Online]. Available: https://github.com/DeustoTech/UroSound

[3] J. Friedman, T. Hastie, and R. Tibshirani, "Additive logistic regression: a statistical view of boosting," The Annals of Statistics, vol. 28, no. 2, pp. 337 – 407

[4] L. Breiman, "Random forests," Machine Learning, vol. 45, no. 1, pp. 5–32, Oct 2001

ACKNOWLEDGEMENTS

This research was supported by the Spanish Ministry of Science and Innovation under the PeaceOfMind project (ref. PID2019-105470RB-C31). A special thank you to all the volunteers patients that participated in our clinical study.

CONTACT INFORMATION

Girish Narayanswamy: girishvn@uw.edu

Laura Arjona: laura.arjona@deusto.es