

Experimental Sensitivity Analysis for LVAD Obstruction Detection Using Acoustic Sensing

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ABSTRACT

This research explores the sensitivity of sensor selection, flow rate, and phantom tissue thickness associated with a simplified left ventricular assist device (LVAD) system. Previous studies have applied obstruction detection methods for LVADs in mock circulatory loops, however, insight into the design considerations of the experimental setup related to variation in operating conditions is missing. The goal of this research is to assess the sensitivity of obstruction detection in a simplified flow setting to inform the experimental design of LVAD studies and further the development of an AI-enabled digital stethoscope. Acoustic recordings were collected using two digital stethoscopes for several operating conditions, including three occlusion severities (0%, 25%, and 50% by diameter), three phantom tissue thicknesses (6.35, 12.7, and 19.05 mm), and three flow rates (2, 5, and 10 LPM). Recordings from each sensor were recorded in separate instances to assess variability and repeatability. The dataset was used to characterize the influence of severity, flow rate, and attenuation on the relevant condition monitoring signals. Frequency domain features were extracted and used to train support vector machine (SVM) and random forest (RF) models. The second part of the study considers pulsed flow, which is closer to the reality of LVAD operating conditions, where the flow through the LVAD is dependent on the pressure drop across the pump, which is highly influenced by native heart function. Here, the continuous wavelet transform (CWT) was applied to the acoustic measurements to analyze the time-frequency domain at specific regions of interest. Spectral features were extracted from the CWT regions and were used to train SVM and RF models. Detection of obstructions is sensitive to sen-

sor selection, and the operating condition boundaries of each sensor are apparent. The custom sensor is more sensitive to changes in flow rate. Conversely, the commercially available sensor is more sensitive to changes in tissue thickness. This work will directly inform experimental design decisions for a custom mock circulatory loop LVAD study and provide the basis for the development of an AI-enabled stethoscope specifically for LVADs.

1. INTRODUCTION

Heart failure (HF) affects millions of Americans, an estimated 6.7 million Americans over 20 years old have HF. This figure is expected to reach over 11 million by 2050 (Bozkurt et al., 2025). The total costs of HF is estimated to reach \$420 billion by 2050 (Fonarow et al., 2026) with an average cost of \$32,955 in 2017-2018 per patient (Bhatnagar, Fonarow, Heidenreich, & Ziaeian, 2022). One method of HF treatment is left ventricular assist devices (LVADs) with approximately 2500 devices used per year since 2013 (Bozkurt et al., 2025). An estimated 100,000 to 300,000 Americans are eligible for LVAD therapy (Lee, Fukamachi, Golding, Moazami, & Starling, 2013). While life-saving, LVAD dysfunction is possible and can pose risk to patient well-being.

This research aims to develop a system capable of detecting and rating the severity of blockage level in a mock circulatory system that includes an LVAD. LVADs are implanted in heart failure (HF) patients to pump blood from the left ventricle into the ascending aorta. They have shown promise in treating patients as a temporary solution for patients waiting for a transplant and as a permanent solution for patients who are ineligible for transplants (Lee et al., 2013). As with any mechanical system, they can fail or induce negative changes to the blood or cardiovascular system. One failure mode is the formation of a blockage within the pump or at the aor-

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tic graft site, which can be detrimental to patients (Reuter, 2019). The detection of these obstructions non-invasively and at low-cost would have a significant benefit to patient well-being. Previous researchers have studied some common failure modes in LVADs and shown success in the diagnosis of failures via acoustic analysis. Aortic regurgitation is one failure condition that is characterized by blood leaking past the aortic valve. Misumi et al. developed a method for detecting aortic regurgitation in LVAD patients for a specific device, the Jarvik2000. They report an accuracy of 91% and a true positive rate of 75% using a discrete wavelet method to extract features from the audio and an ensemble classifier (Misumi et al., 2021). Semiz et al. focused on detecting pump thrombosis in LVADs using acoustic analysis. They utilize the Spearman correlation coefficient to rank features based on the correlation between blood biomarkers and frequency. The results of this method are 88.9% accuracy, 90.9% sensitivity, and 83.3% precision (Semiz et al., 2020). Both methods require access to LVAD patients and require more stringent data collection procedures. In this study, we investigate the use of classification algorithms applied to the raw acoustic signature of a digital stethoscope. Past studies have shown analysis of acoustic signals using algorithms such as Support Vector Machine (SVM), Random Forest (RF) (Misumi et al., 2021; Bordoloi & Tiwari, 2017; Prechtl, Day, & Kolodziej, 2018), naïve Bayes (Misumi et al., 2021), logistic regression (Semiz et al., 2020), and neural networks (Baronti, Castellani, Hefft, & Alberini, 2022; Kim et al., 1995).

Stroke occurrence is a severe complication of LVAD implantation. Stroke can occur from the development of obstructions in the LVAD inlet region, damage to the blood in the pump, obstruction at the pump outlet region, or infection (Vaidya, Riaz, & Dhamoon, 2025). Previous work has achieved inlet blockage identification using accelerometers, pressure transducers, and current probes (Kumar, 2023). However, the identification of pump blockages non-invasively could improve patient outcomes. Therefore, it is of interest to develop a detection system using common tools available to medical professionals, such as stethoscopes. Stethoscopes have been used in cardiology for decades, and there have been many studies investigating the analysis of heart sounds. Acknowledgment of the non-stationary nature of heart sounds has been accepted since the 1950s (Wood & Barry, 1995). Since then, studies have explored various means to analyze heart sounds in the time-frequency domain. Wood and Barry illustrate that non-stationary signal analysis is typically applied to the study of mechanical prosthetic valves. They claimed that a greater understanding of the first heart sound mechanics was required to diagnose native valve pathology (Wood & Barry, 1995). In recent years, the adoption of machine and deep learning methods has created interest in the application to heart sound analysis (Zhao et al., 2024). Heart sound analysis is enabled by listening to the heart through stethoscopes.

The use of stethoscopes by physicians for heart sound auscultation and diagnosis is subject to the experience of the physician and the stethoscope being used. Two types of stethoscopes are available: passive, which have no amplification capability, and active, which can amplify sound. Passive stethoscopes are limited to heart sounds in the 50-600 Hz range. Active stethoscopes are capable of detecting heart sounds in the 1-10,000 Hz range (Parke, 2020). For active stethoscopes, sound amplification is achieved using a microphone. Consideration of impedance is critical in stethoscope design, where the impedance of the microphone should closely match that of the skin. One design choice is a piezoelectric microphone coupled with a gel on the skin (Parke, 2020).

Mock Circulatory Loops (MCL) provide a means for scientists and physicians to evaluate artificial hearts and LVADs with less need for animal testing, which are costly and surrounded by ethical issues (Gwak, 2015). MCL design depends on the devices to be tested and the physiology of the system to be studied. For LVAD testing, the MCL typically consists of a left ventricle, Aortic compliance, systemic resistance, venous reservoir, an LVAD, and a pneumatic or hydraulic mechanism to drive the left ventricle. Due to the many types of simulators and complex signals present in such simulators, it is of interest to simplify the system further to a flow loop consisting of a pump and various obstructions to study the pump system without the native heart and focus on the acoustic signature of obstructions. The objective of this study is to quantify the effect of phantom tissue thickness, flow rate, and sensor selection on the classification of obstruction size.

2. METHODS

2.1. Constant Flow Experiment

A simplified flow bench was designed illustrated in Figure 1.

Water was pumped through a half-inch tube and into the blockage region. The blockage region was encased in silicone to mimic human tissue ($\frac{1}{4}$ ", $\frac{1}{2}$ ", $\frac{3}{4}$ "). The material chosen for the tissue phantom is Ecoflex 00-10 silicone rubber, this material has been used in previous studies and established as a suitable tissue phantom (Reuter, 2019; Prechtl et al., 2018; Yost, Royston, Bhat, & Tatoes, 2016). Three thicknesses were chosen to evaluate the attenuation of the tissue phantom. The obstructions were 3D printed cylinders with $\frac{1}{2}$ " outer diameter and inner diameters of $\frac{3}{8}$ ", and $\frac{1}{4}$ ". The unobstructed case was also considered, resulting in occlusions of 0%, 25%, and 50% by diameter. These levels are chosen to capture varying levels of severity. The flow rates tested were 2, 5, and 10 LPM to capture the target cardiac output of a healthy patient, low flow condition, and exercise condition (D'Souza et al., 2023). Flow rate was measured using an ultrasonic flow meter (em-tec GmbH, Finning, Germany).

For each test condition (obstruction size, tissue phantom

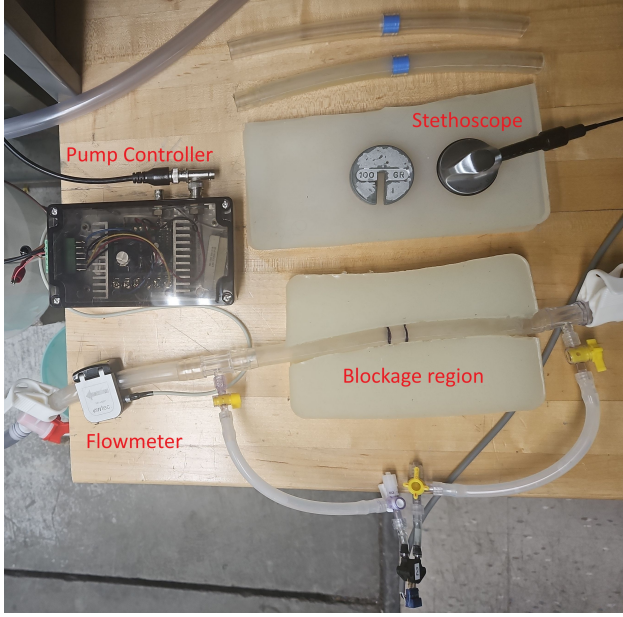


Figure 1. Experimental setup for acoustic measurements.

thickness, flow rate), acoustic signals were recorded using a digital stethoscope (Thinklabs One, Centennial, CO) and a custom digital stethoscope sampled at 44 kHz. A 100-gram mass was placed on the sensor to simulate physician application pressure. Data was collected in two separate instances: 40 seconds of acoustic data were recorded as training data, and 20 seconds were recorded as test data. This was done to minimize overfitting of the models and temporal correlation effects. The custom digital stethoscope utilized an off-the-shelf medical-grade stethoscope (Littmann Master Classic II) and an omnidirectional condenser microphone (Audio-Technica AT803B) paired with an active audio adapter (Beechtek DXA-MICRO Pro). The custom stethoscope system is illustrated in Figure 2. Ultrasound transmission gel was applied to the sensor tissue interface for all audio recordings. For each stethoscope, the training set includes 1080 data points (360 per class), and the test set has 540 data points (180 per class).

2.2. Pulsed Flow Experiment

Consideration of dynamic flow through the orifice was also considered. The same experimental setup was used for the constant flow condition. The flow rate through the orifice was pulsed between two conditions, 2-5 LPM and 2-10 LPM. Here, a single tissue thickness of 12.7 mm was used. Here, 60 seconds of data were recorded for each condition for the training set and repeated in a separate setup for the testing set. The total number of training points for each stethoscope is 348 (116 per class). The number of test points is a different set of 348 points (116 per class). Audio was recorded at the blockage region using the same sampling parameters as



Figure 2. Custom stethoscope used in the experiment, including audio pre-amp, audio amplifier, digital microphone, and stethoscope.

before. Figure 3 illustrates an example of the data recorded for the experiment. Distinct changes in the audio signal at the flow peaks are observed. An accelerometer was attached to the system near the pump to measure the frequency of vibration of the pump for the pulsed flow study. This signal can be used to identify the operating frequency range of the pump to investigate the effect of vibration on the classification model.

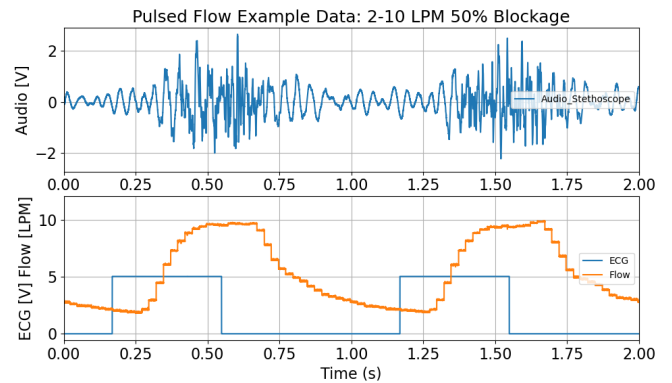


Figure 3. Example data for the pulsed flow experiment at 60 BPM. The audio recording is shown in the top plot. The flow rate and pump trigger (ECG) signals are shown in the bottom plot.

3. ACOUSTIC SIGNAL PROCESSING

3.1. Constant Flow Acoustics

Each recording was first segmented into 1-second blocks, and these blocks were aligned at 0 seconds. Next, the Fast Fourier Transform (FFT) was applied to each audio signal block. The resulting signal was analyzed between 0 and 100 Hz because there was little to no frequency content past 100 Hz. The signal was then binned into 50 bins of 2 Hz each. The magnitude of each bin was then averaged, resulting in feature vectors of 50 binned frequency features shown in Figure 4.

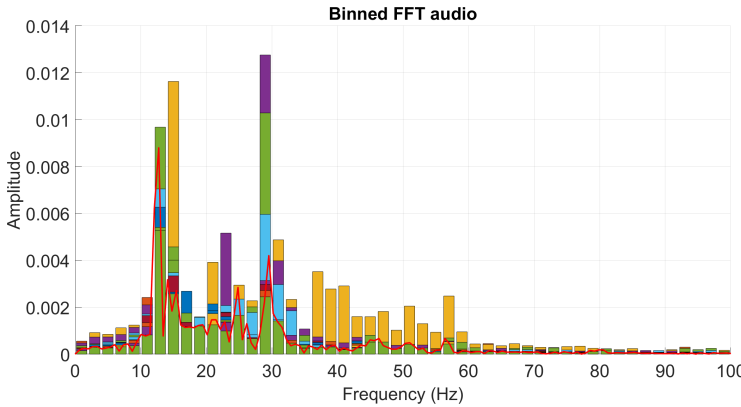


Figure 4. Binned FFT for the constant flow condition at 5 LPM with 25% blockage at 6.35 mm tissue thickness.

Principal component analysis (PCA) was implemented following signal processing to reduce the feature space and capture the highest variance components for classification. PCA and scaling were fitted using only the training set. A variance tolerance of 0.9 is chosen for the PCA step to capture 90% of the variance and ensure the most significant patterns are retained. Next, an SVM algorithm was trained to classify the occlusion levels. PCA reduces the feature space from 50 frequency magnitude features to those that are more informative for the classification problem. PCA has many uses in machine learning (ML) and serves to reduce the number of features and capture distinct information from the original feature space. The principal components are linear combinations of the initial features (Cao, Hu, Luo, & Wang, 2021). Each component captures a segment of the total variation in the signal and prioritizes components with higher variation, thus reducing the feature space while retaining components with more information about the signal.

SVM is widely used and has shown promise in detecting both LVAD (Precht et al., 2018) and centrifugal pump failure modes (Bordoloi & Tiwari, 2017). Precht et al. used a CWT and SVM analysis on a hemodynamic simulator to detect blockages in the system. While similar to this work, a sensitivity analysis of the experimental variables was not performed. They report a classification accuracy of up to 92% using an SVM with a 7th degree polynomial kernel. Bordoloi

and Tiwari diagnosed blockage levels and cavitation events in centrifugal pumps. Their methods leveraged SVM applied to statistical features from vibration signals. SVM is an algorithm that can map the input feature space to a higher-dimensional space where a linear decision boundary exists and ensures high generalization ability (Cortes & Vapnik, 1995). Meaning the algorithm can offer good performance on new data (Vapnik, 1999). The core principle of SVM is creating a support vector network based on the boundary of each class, then constructing a hyperplane between the class boundary support vectors, and maximizing the separation between the hyperplane and each class (Cortes & Vapnik, 1995). SVM classifiers are used in several centrifugal pump applications (Rapur & Tiwari, 2019; Muralidharan, Sugumaran, & Indira, 2014; Panda, Rapur, & Tiwari, 2018; Altobi, Bevan, Wallace, Harrison, & Ramachandran, 2019).

Several classifications were performed for the constant flow case. First, the flow rate and phantom tissue thickness were fixed with the obstruction size varying. For example, a model was trained on data at 2 LPM with 6.35 mm tissue thickness. This was repeated for each flow rate and tissue thickness. To test the models, the trained model was tested on a different dataset with the same flow rate and thickness. Then the model was tested by varying the flow rate and tissue thickness. The purpose of this was to assess the sensitivity of the model to variables it was not trained on. Next, a leave-one-out approach was implemented where the model was trained on data without one flow rate or tissue thickness at a time and tested on all variables. Lastly, a model was trained with all variables, including the three obstructions, flow rates, and tissue thicknesses. For each model trained, a grid search optimization was implemented. Wherein, a 5-fold cross-validation mechanism was used (80% train, 20% validation). Sixteen models were trained on the constant flow data. Six models were trained on the pulsed flow data.

3.2. Pulsed Flow Acoustics

For the more interesting pulsed flow study, the data contains a triggering channel that can be leveraged to segment the data, analogous to an ECG signal from a cardiac patient. The trigger point was the start of the flow pulse; this trigger was offset by 100 ms to capture a portion of the preceding segment. This was done to mimic what is planned for the clinical setting, as the previous heartbeat affects the next and is important in the analysis for condition assessment. The end of the segment is the period of the ECG signal minus the offset. At 60 BPM, this equates to the segment ranging from 100 ms before the rising edge of the square wave to 900 ms past the edge. This results in 0% overlap between segments. Each one is first normalized prior to being point-by-point averaged to generate the ensemble-averaged cycle sound of 60 cycles. This process is illustrated in Figure 5. The top plot is the raw audio signal with the red points corresponding to the trigger

locations. The middle plot shows each segment overlaid with the trigger location noted in the vertical red dashed line. The bottom plot is the ensemble average of each segment with the same red dashed line. The recorded audio was played back, and a distinct flow sound was audible for the 2-10 LPM condition for both the 25% and 50% blockage. This sound was not distinctly audible at 2-5 LPM.

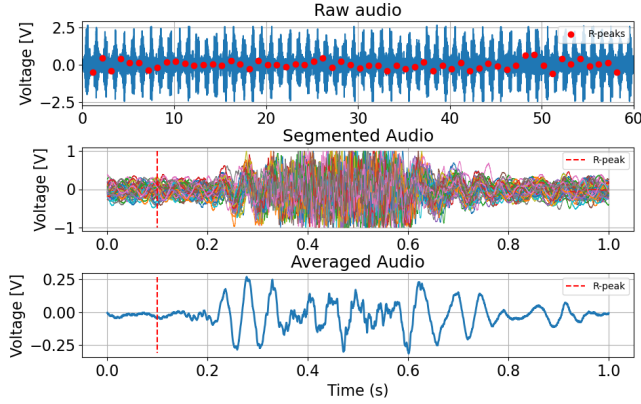


Figure 5. Audio segmentation and averaging.

Next, the continuous wavelet transform was applied to the acoustic signals to analyze the time-frequency spectra of the signals. The CWT was applied using the *ssqueezepy* package in Python with a *cmhat* wavelet. This wavelet was chosen because it provides a balance between time and frequency resolution. Following initial time-frequency analysis, the effect of pump vibration was considered. First, the averaged audio signal was observed as shown in Figure 6. Here, the majority of the signal intensity was below 70 Hz, with some signal energy above this range.

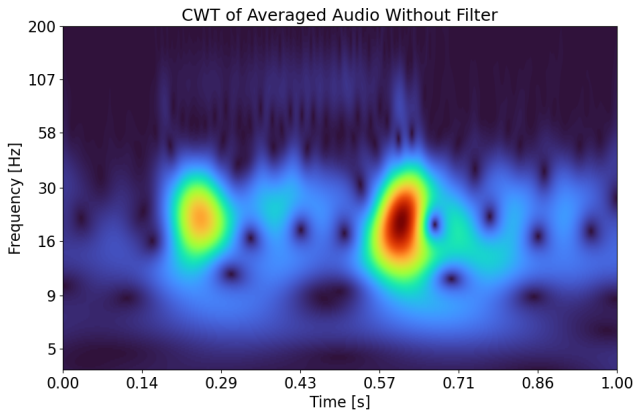


Figure 6. CWT of the averaged audio signal using the Custom stethoscope at 2-10 LPM flow rate with 25% blockage.

The accelerometer signal was assumed to be the cause of this faint noise. This was confirmed when observing the CWT of the accelerometer signal illustrated in Figure 7, one can see that the most intense frequency content lies at the 70 Hz mark.

Thus, the audio signal was low-pass filtered. The filtered audio signal is shown in Figure 8. This minimally affects the CWT of the audio signal, and when playing back the filtered sound, there is still an audible murmur present. This is the final preprocessing step prior to feature extraction.

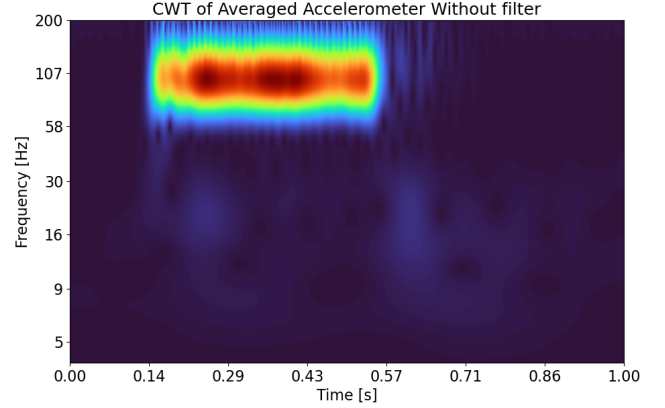


Figure 7. CWT of the averaged accelerometer signal.

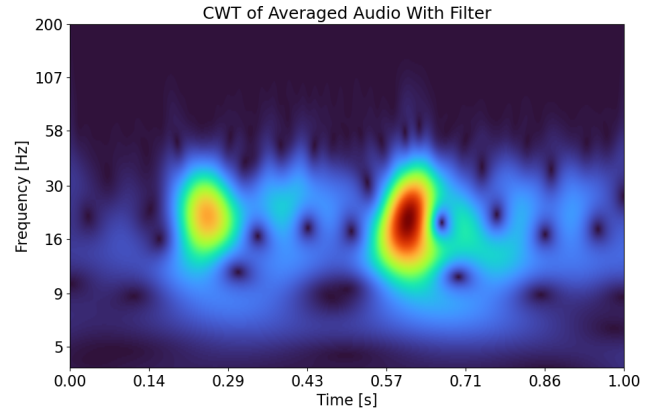


Figure 8. CWT of the averaged audio signal with a 70 Hz low-pass filter applied. Using the Custom stethoscope at 2-10 LPM flow rate with 25% blockage

Regions of interest were identified to be at the start and end of the flow through the obstruction. Each region of interest was analyzed individually by computing the CWT again for each region. Frequency features were then extracted from the CWT coefficients. This is done for each cycle. The list of features extracted is summarized in Table 1. The features were selected based on a previous study (Precht et al., 2018). The regions are analogous to systole and diastole in the cardiac cycle. These regions correspond to the S1 and S2 heart sounds in a phonocardiogram. An example is shown in Figure 9.

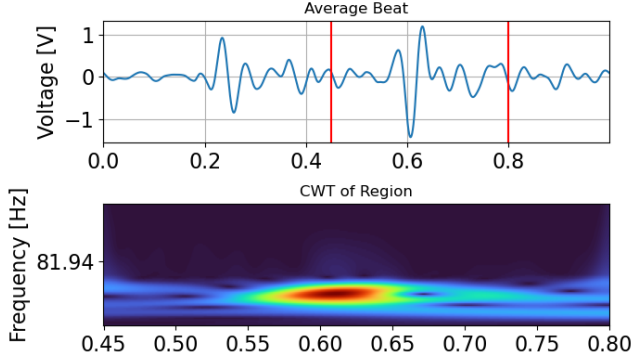


Figure 9. Region of Interest analysis example for one region using the Custom stethoscope at 2-10 LPM flow rate with 25% blockage.

Table 1. Features extracted from regions of interest in the continuous wavelet transform coefficient matrices.

Feature #	Feature
1	Energy
2	Kurtosis
3	Skewness
4	Peak
5	RMS
6	Crest

Features are extracted from the CWT coefficient bands, where each band is the magnitude of the CWT coefficient matrix W . The feature equations are shown in Equations 1-8. Where $W(a, b)$ represents the CWT coefficients at scale a and time index b . Statistical features are computed for all scales at each time index.

$$Energy(a) = \sum_{b=1}^N |W(a, b)|^2 \quad (1)$$

$$Kurtosis(a) = \frac{\frac{1}{N} \sum_{b=1}^N (|W(a, b)| - \mu(a))^4}{\sigma(a)^4 + \epsilon} \quad (2)$$

$$\mu(a) = \frac{1}{N} \sum_{b=1}^N |W(a, b)| \quad (3)$$

$$\sigma(a) = \sqrt{\frac{1}{N} \sum_{b=1}^N (|W(a, b)| - \mu(a))^2} \quad (4)$$

$$Skewness(a) = \frac{\frac{1}{N} \sum_{b=1}^N (|W(a, b)| - \mu(a))^3}{\sigma(a)^3 + \epsilon} \quad (5)$$

$$Peak(a) = \max_{1 \leq b \leq N} |W(a, b)| \quad (6)$$

$$RMS(a) = \sqrt{\frac{1}{N} \sum_{b=1}^N |W(a, b)|^2} \quad (7)$$

$$CrestFactor(a) = \frac{P(a)}{RMS(a)} \quad (8)$$

4. RESULTS

The results of each method are summarized in this section, first, the constant flow study is assessed, followed by the pulsed flow study. Sensitivity to classification performance is assessed for flow rate, tissue thickness, and sensor selection individually. Additionally, a comparison of the full-parameter models for each stethoscope is included.

4.1. Constant Flow

The results of the constant flow study are summarized in this section for several trained models.

4.1.1. Flow rate Sensitivity

Tables 2 and 3 show the sensitivity of the trained models to changes in flow rate. The training and validation sets resulted in high accuracy of 98-100% for all instances. First, the ML models were trained and validated on a fixed tissue thickness and flow rate of 6.35 mm and 5 LPM. Next, the models were tested against a separate dataset at the specified tissue thickness for each flow rate (2, 5, and 10 LPM). The model hyperparameters are shown in Table 4. The models were retrained on the next tissue thickness, and the process was repeated. The results of this analysis show that the classification accuracy is affected by changes in flow rate. This suggests that including multiple flow rates in the training dataset for future LVAD studies is required.

Table 2. Flow rate sensitivity test set accuracy. Rows marked with * indicate training instances.

Thickness [mm]	LPM	Custom	Thinklabs
6.35	2	51.7%	66.7%
*6.35	5	98.3%	93.3%
6.35	10	66.7%	35.0%
12.7	2	41.7%	60.0%
*12.7	5	98.3%	93.3%
12.7	10	43.3%	66.7%
19.05	2	35.0%	66.7%
*19.05	5	98.3%	65.0%
19.05	10	50.0%	65.0%

Table 3. Flow rate sensitivity test set performance metrics. Rows marked with * indicate training instances. C and T denote Custom and Thinklabs sensors, respectively.

C Pre.	C Recall	C F1	T Pre.	T Recall	T F1
35.2%	51.7%	41.9%	44.6%	66.7%	53.4%
*98.4%	98.3%	98.3%	93.6%	93.3%	93.3%
50.0%	66.7%	55.6%	50.0%	35.0%	25.4%
39.8%	41.7%	33.8%	48.8%	60.0%	51.4%
*98.4%	98.3%	98.3%	93.9%	93.3%	93.3%
27.3%	43.3%	33.4%	50.0%	66.7%	55.6%
18.7%	35.0%	24.2%	50.0%	66.7%	55.6%
*98.4%	98.3%	98.3%	49.6%	65.0%	54.3%
47.5%	50.0%	42.1%	50.0%	65.0%	54.7%

Table 4. Model regularization coefficients for Custom and Thinklabs configurations. All models used a linear SVM.

Training parameters	Custom	Thinklabs
5 LPM, 6.35 mm	1	0.1
5 LPM, 12.7 mm	0.1	0.1
5 LPM, 19.05 mm	0.1	1

4.1.2. Tissue Thickness Sensitivity

The sensitivity of classifier performance on tissue thickness is shown in Tables 5 and 6. The model parameters are shown in table 7. Similar to flow rate, the classification accuracy is sensitive to changes in tissue thickness, primarily at low flow rates where the signal-to-noise ratio is lower.

Table 5. Tissue thickness sensitivity test set accuracy. Rows marked with * indicate training instances.

Flowrate [LPM]	Thickness [mm]	Custom	Thinklabs
*2	6.35	83.3%	86.7%
2	12.7	41.7%	73.3%
2	19.05	36.7%	53.3%
*5	6.35	98.3%	93.3%
5	12.7	36.7%	100.0%
5	19.05	60.0%	50.0%
*10	6.35	43.3%	98.3%
10	12.7	33.3%	91.7%
10	19.05	33.3%	58.3%

Table 7. Model regularization coefficients for Custom and Thinklabs configurations. All models used a linear SVM.

Training parameters	Custom	Thinklabs
2 LPM, 6.35 mm	0.1	0.1
2 LPM, 12.7 mm	1.0	0.1
2 LPM, 19.05 mm	0.1	0.1

To further investigate the sensitivity to flow rate and tissue thickness, models were trained using a leave-one-out approach where one flow rate or tissue thickness was left out of

Table 6. Tissue thickness sensitivity test set performance metrics. Rows marked with * indicate training instances. C and T denote Custom and Thinklabs sensors, respectively.

C Pre.	C Recall	C F1	T Pre.	T Recall	T F1
85.0%	83.3%	82.1%	86.7%	86.7%	86.7%
25.7%	41.7%	31.6%	73.7%	73.3%	69.4%
48.8%	36.7%	27.2%	74.3%	53.3%	45.3%
*98.4%	98.3%	98.3%	93.6%	93.3%	93.3%
20.6%	36.7%	26.2%	100.0%	100.0%	100.0%
42.6%	60.0%	49.4%	33.3%	50.0%	40.0%
50.0%	43.3%	37.6%	98.4%	98.3%	98.3%
13.6%	33.3%	19.3%	93.3%	91.7%	91.5%
11.1%	33.3%	16.7%	50.0%	58.3%	50.8%

the training data. The results of the leave-one-out approach are summarized in Tables 8 and 9.

Table 8. Flow rate leave-one-out test set performance by sensor. All models used a linear SVM with $C = 1$.

Left out	Sensor	Acc.	Pre.	Recall	F1
2 LPM	Custom	76.4%	80.7%	76.4%	73.2%
	Thinklabs	83.6%	83.9%	83.6%	82.9%
5 LPM	Custom	56.7%	67.2%	56.7%	53.5%
	Thinklabs	70.6%	71.3%	70.6%	70.7%
10 LPM	Custom	68.9%	75.1%	68.9%	67.0%
	Thinklabs	57.2%	76.2%	57.2%	52.1%

Table 9. Tissue thickness leave-one-out test set performance by sensor. All models used a linear SVM with $C = 1$.

Left out	Sensor	Acc.	Pre.	Recall	F1
6.35 mm	Custom	69.2%	69.9%	69.2%	67.8%
	Thinklabs	50.0%	54.5%	50.0%	45.6%
12.7 mm	Custom	79.2%	79.4%	79.2%	77.9%
	Thinklabs	63.6%	71.7%	63.6%	63.2%
19.05 mm	Custom	82.8%	84.8%	82.8%	83.1%
	Thinklabs	53.3%	67.5%	53.3%	49.3%

4.1.3. Full Parameter models

Next, the full parameter models are assessed. Each model is trained on the full array of data variables, including three obstructions, three tissue thicknesses, and three flow rates. Rather than isolating one flow rate and tissue thickness. The testing set results are illustrated in Table 10.

Confusion matrices for SVM models generated from the constant flow testing set are illustrated in Figures 10 & 11. The custom sensor performs well on the unobstructed and severely obstructed classes and has difficulty with the middle obstruction class. The Thinklabs sensor detects the severe obstruction well. However, it struggles with distinguishing the middle class from the others.

Table 10. Full parameter model test set performance. SVM models used a linear kernel with $C = 1$. Random forests used max depth = 20, max features = $\sqrt{\cdot}$, and 500 estimators for the custom sensor data and 100 estimators for the Thinklabs.

Sensor	Model	Acc.	Pre.	Recall	F1
Custom	SVM	73.7%	73.5%	73.7%	73.6%
	RF	73.1%	73.8%	73.1%	73.3%
Thinklabs	SVM	60.0%	70.0%	60.0%	57.6%
	RF	44.6%	60.1%	44.6%	37.5%

Constant Flow: Custom Sensor SVM Full Parameter Model

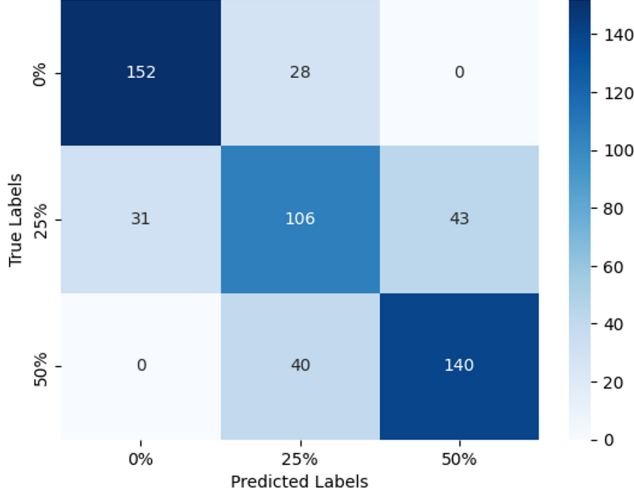


Figure 10. Constant flow test set results for the custom sensor full parameter model. SVM, linear kernel, $C=1$.

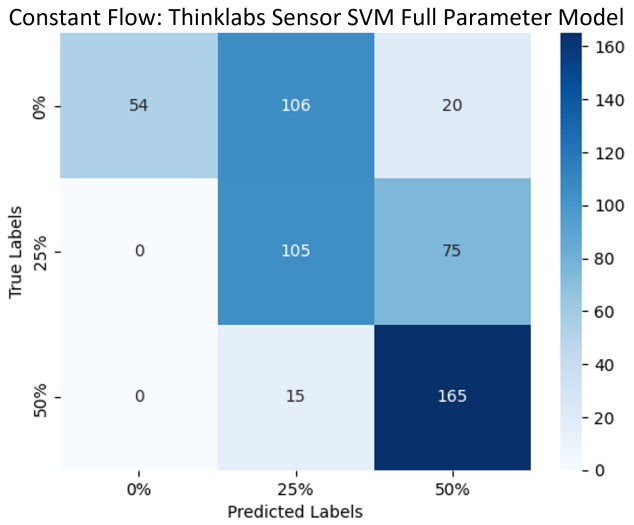


Figure 11. Constant flow test set results for the Thinklabs sensor full parameter model. SVM, linear kernel, $C=1$.

The constant flow results highlight the sensitivity of flow rate, tissue thickness, and sensor selection on classification accu-

racy. The baseline models trained on one flow rate and tissue thickness are unable to generalize well to unseen data with varying tissue thickness or flow rate. The models trained on data with all variables illustrate that the custom stethoscope achieves higher classification accuracy than Thinklabs for the selected classifiers. The results highlight the importance of creating a representative dataset for future studies. When moving to the hemodynamic simulator, this should be carefully considered in the study design to include an array of simulated patients to ensure the ML models can generalize well to variability in unseen data. The custom sensor performs well in the leave-one-out approach, which suggests the models can generalize well on unseen data.

4.2. Pulsed Flow

The pulsed flow condition included a single tissue thickness of 12.7 mm with 2 flow rate ranges (2-5 LPM, 2-10 LPM). The objective is to investigate how dynamic flow affects the murmur generated by flow through the orifice levels. Table 11 shows the classification training and validation results for models trained on obstruction data for each pulsed flow rate separately. The test set results are shown in Table 12. The model hyperparameters determined are illustrated in Table 13. The model training and validation performance results in high accuracy and consistent metrics. However, the testing results show decreased performance, indicating the models are overfit to the training dataset and unable to generalize well, especially at the low flow rate for the custom sensor. The Thinklabs sensor generalizes better at the 2-5LPM flow rate. The steep decrease in accuracy at the low flow rates may stem from a low signal-to-noise ratio, suggesting the measurement system requires further investigation for low flow rates, and tissue-mimicking phantoms may be necessary for the obstruction design.

Table 11. Pulsed flow obstruction classification training and validation performance with tissue thickness of 12.7 mm.

Sensor	LPM	Train	Val. Acc.	Val. P/R/F1
Custom	2-5	100%	100.0%	100/100/100
Thinklabs	2-5	100%	94.7%	95/95/95
Custom	2-10	100%	100.0%	100/100/100
Thinklabs	2-10	99.1%	100.0%	100/100/100

Table 12. Flow rate model test set performance across training ranges.

Sensor	LPM	Acc.	Pre.	Recall	F1
Custom	2-5	33.0%	11.0%	33.3%	16.5%
Thinklabs	2-5	64.4%	49.4%	64.4%	54.5%
Custom	2-10	67.2%	83.5%	67.2%	56.8%
Thinklabs	2-10	71.3%	84.6%	71.3%	70.6%

Table 13. SVM hyperparameters for flow rate model training. All models used an RBF kernel.

Sensor	LPM	C	γ
Custom	2–5	10	0.1
Thinklabs	2–5	1	scale
Custom	2–10	10	0.1
Thinklabs	2–10	0.1	scale

Four models are trained and tested on both flow rates to assess the model's ability to differentiate between classes. Training and validation performance metrics are shown in Table 14. The test performance results are shown in Table 15. The corresponding confusion matrices for SVM models are shown in Figures 12 & 13.

Table 14. Model training and validation performance using both flow rates. Validation P/R/F1 reports precision, recall, and F1 score, respectively.

Sensor	Model	Train Acc.	Val. Acc.	Val. P/R/F1
Custom	SVM	100%	99.1%	99/99/99
	RF	100%	99.1%	99/99/99
Thinklabs	SVM	100%	97.4%	97/97/97
	RF	100%	95.7%	95/95/95

Table 15. Model test set performance by sensor for pulsed flow data with both flow rates.

Sensor	Model	Acc.	Pre.	Recall	F1
Custom	SVM	47.4%	52.2%	47.6%	46.7%
	RF	49.1%	52.7%	49.3%	48.3%
Thinklabs	SVM	67.0%	83.4%	67.0%	56.2%
	RF	65.5%	83.1%	65.5%	55.1%

Table 16. Optimized hyperparameters for the SVM and RF models.

Sensor	Model	Parameter	Value
Custom	SVM	C	10
		γ	scale
		Kernel	RBF
	RF	Max depth	20
		Max features	$\log_2$
Thinklabs	SVM	$n_{est.}$	200
		C	1
		γ	scale
	RF	Kernel	RBF
		Max depth	5
		Max features	$\sqrt{\cdot}$
		$n_{est.}$	100

The custom sensor models have difficulty distinguishing between the middle obstruction and the other classes. Additionally, the models struggle to distinguish between severely

obstructed and unobstructed. This is similar to clinical stenosis diagnosis in some cases, a severely obstructed blood flow path is misdiagnosed as a normal or healthy condition. Furthermore, stenosis is often clinically classified as at least mild, or at least moderate-severe. Class separability is difficult in this setting as well. The models generated from the Thinklabs sensor data perform very well at the severe obstruction but are unable to distinguish between unobstructed and a mild obstruction. This provides confidence in the ability to detect severe obstructions. The poor class separability for the mild obstruction may be in part because of non-linear flow dynamics with a changing obstruction size.

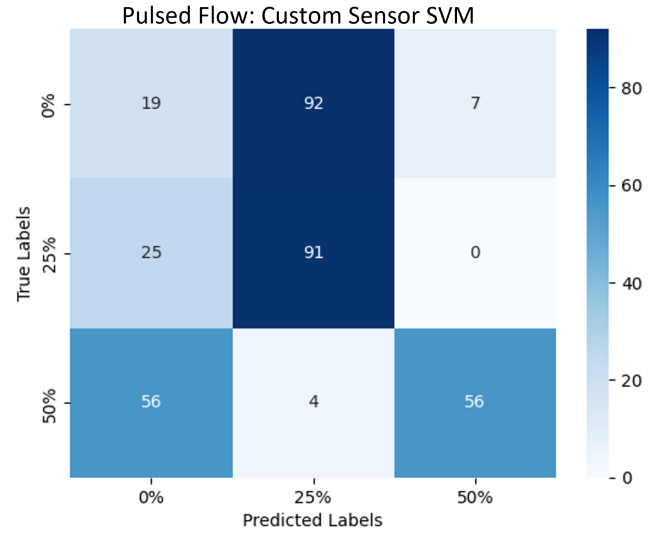


Figure 12. Pulsed-flow results for the custom sensor data. SVM: $C=10$, $\gamma=scale$, kernel=rbf

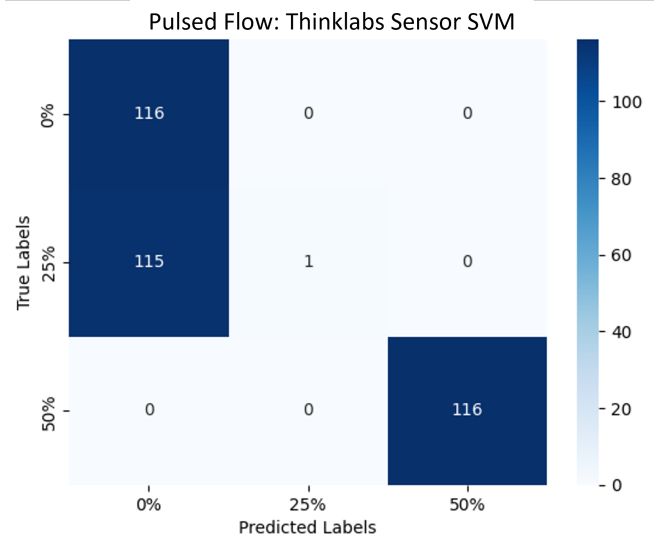


Figure 13. Pulsed flow results for the thinklabs sensor data. SVM: $C=1$, $\gamma=scale$, kernel=rbf

Both sensors result in good classification accuracy at the higher flow rate; however, the custom sensor performs poorly on the low flow rate. This is likely a result of low signal-to-noise ratio at low flow rates coupled with manually tuning the amplifier gain on the custom sensor, and future studies should include an analysis of the sensor amplification parameters and an assessment of the audible murmur quality as well as adaptive filtering measures and consideration of tissue-mimicking materials for obstructions. Future studies are in progress to assess the measurement system and validate that the audio recorded from the custom sensor is adequate. This is imperative to capture the heart sounds from the hemodynamic simulator effectively. Overall, the results provide confidence that obstruction detection is possible in both constant and pulsed flow conditions.

5. CONCLUSION

Detection and classification of occlusions is possible based on acoustic signals. Although demonstrated here on a simple loop, the methods can be expanded to a hemodynamic simulator with pulsed flow through an obstruction. Additionally, models developed on the simulator will be subject to more in-depth hyperparameter optimization. One limitation of the current study is in the machine learning algorithms. More intricate methods, such as transfer learning, will be investigated. The primary lessons learned from this study will inform the design of the experiments for the simulator by influencing the data collection plan to include variability in patient-specific parameters such as flow rate, heart rate, and tissue thickness. The constant flow results indicate the custom stethoscope is more sensitive to changes in flow rate, while the Thinklabs stethoscope is more sensitive to changes in tissue thickness. The pulsed flow results show that obstruction detection is possible in a time-varying system and provides confidence the methods can be applied to the hemodynamic simulator to further the development of an AI-enabled digital stethoscope. The next phase of this research is to adapt the signal processing methods to the hemodynamic simulator and investigate both time and frequency feature extraction methods applied to acoustic recordings on the simulator. Furthermore, the results of this study suggest the need to investigate feature-level normalization such as dynamic range compression, Z-score and peak normalization, or similar, as well as adaptive filtering mechanisms to address variations in signal attenuation across diverse patient body types.

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