Figure 1: A. This image shows a normal breath at breath #213 followed by two coughs in quick succession. Cough can usually be visually identified by sharp inhalation and exhalation spikes in the flow waveform (blue). B. Here, we show a series of suction events from breath #172 to #176. Suction artifact results from repeated triggering of breath delivery by the suction catheter, evidenced by multiple breaths delivered in succession without substantive exhalation in between breaths.51

Figure 2: A canonical example of a DTA observation. In the first breath, the patient demands additional support beyond what the ventilator is programmed to deliver, resulting on patient-ventilator asynchrony. Ongoing inspiratory effort at the end of the first breath causes a new breath to be triggered without intervening exhalation, resulting in dynamic hyperinflation and potential lung injury. DTA, double trigger asynchrony

Figure 3: An example of BSA. In BSA, a patient attempts to exhale but expiratory time is too short to allow full exhalation in between successive breaths, resulting in dynamic hyperinflation. In this study, we define any morphologically normal breath where TVe/TVi < 0.9 and E-time > 0.3 seconds as BSA. In this case, the TVe/TVi is 0.7 and the E-time is 1.1 seconds, which we qualify as a breath stacking event. BSA, breath stacking asynchrony; TVe/TVi, expiratory divided by inspiratory tidal volume; E-time, expiratory time (seconds).

Figure 4: Chi-square sensitivity analysis for DTA without SMOTE. Our analysis suggests optimal model performance using all 16 metadata features. Note the low DTA sensitivity of this model when SMOTE is not used.. DTA: double trigger asynchrony, SMOTE: synthetic minority over-sampling technique.

Figure 5: Chi-square test with sensitivity analysis detecting BSA without SMOTE. We found all 16 features to be the optimal number of features to be used. BSA: breath stacking asynchrony; SMOTE: synthetic minority over-sampling technique.

Figure 6: A. DTA detection models using all metadata features and SMOTE. GBC yields the best model with 70% sensitivity, while other classifiers yield inferior models. B. Using expert-derived features, DTA detection improves with all algorithms, but still could use improvement. SMOTE: synthetic minority over-sampling technique; DTA: double trigger asynchrony; ERTC: extremely randomized trees classifier; GBC: gradient boosted classifier; MLP: multi-layer perceptron; RF: random forest

Figure 7: A. BSA detection using all metadata as features. Here, our feature set performs very well in all classifier algorithms with the exception of the ERTC. B. BSA detection using expert derived features. Here, our highest performing algorithms exhibit equivalent performance to the metadata model, while the ERTC improves its sensitivity score. BSA, breath stacking asynchrony; ERTC, extremely randomized trees classifier; GBC, gradient boosted classifier; MLP, mulit-layer perceptron; RF, random forest.

Figure 8: The use of a simplified dataset including retrospective, expert-derived features improves DTA sensitivity in some models with minimal effect on specificity. A. Models useing the set of 21 features chosen by Chi-square analysis. B. Model using the set of retrospective expert features. The features used here were TVe/TVi, TVe/TVi-previous, E-time-previous. DTA: double trigger asynchrony; TVe: expiratory tidal volume; TVi: inspiratory tidal volume; TVe/TVi: expiratory divided by inspiratory tidal volume; E-time: total expiratory time (seconds). TVe/TVi-previous: the previous breath’s TVe/TVi; E-time-previous: the previous breath’s E-time. ERTC: extremely randomized trees classifier; GBC: gradient boosted classifier; MLP: multi-layer perceptron; RF: random forest

Figure S1: Binary DTA detection using metadata features without SMOTE.DTA: double trigger asynchrony;SMOTE: synthetic minority over-sampling technique.

Figure S2: Binary DTA detection using expert feature without SMOTE.DTA: double trigger asynchrony;SMOTE: synthetic minority over-sampling technique.

Figure S3: Binary DTA detection using retrospective and metadata feature without SMOTE. DTA: double trigger asynchrony;SMOTE: synthetic minority over-sampling technique.

Figure S4:Binary DTA detection with expert retrospective features and run without SMOTE.DTA: double trigger asynchrony;SMOTE: synthetic minority over-sampling technique.

Figure S5: Chi-square sensitivity analysis for binary DTA detection using all retrospective and metadata features. We found 21 features was the optimal number of features here for a subset of DTA features derived from the retrospective and metadata features. DTA: double trigger asynchrony.

Figure S6: Chi-square sensitivity analysis for binary BSA detection using all retrospective and metadata features. Here we found the optimal number of features was 32, which is all possible features. BSA: breath stacking asynchrony.

Figure S7: Binary BSA detection using all retrospective and metadata features. From this experiment we found the addition of the retrospective features did not improve our model above baseline performance of using all metadata. BSA: breath stacking asynchrony.

Figure S8: Figure details the results of running our final model without SMOTE. Most classifiers with exception of GBC suffer from poor DTA sensitivity, while BSA is relatively unaffected by lack of SMOTE. SMOTE: synthetic minority over-sampling technique; PVA: patient ventilator asynchrony; BSA: breath stacking asynchrony; DTA: double trigger asynchrony; ERTC: extremely randomized trees classifier; GBC: gradient boosted classifier; MLP: multi-layer perceptron