Sleep apnea is a common sleep disorder, which involves cessation of breathing due to obstruction of the upper airway (obstructive) or due to suspension of ventilatory effort (central) during sleep. Currently, sleep apnea is diagnosed using polysomnography (PSG). Breathing events are manually scored by trained sleep technicians, however this is time-consuming, expensive, and prone to subjective interpretation. Thus, the aim of this study was to develop a fully automatic algorithm to detect respiratory events in sleep.

Methods:
Oxygen saturation, nasal pressure (transducer), oral airflow (thermistor), respiratory effort (RIP belts), and snoring signals were extracted from 2,366 PSGs from the Wisconsin Sleep Cohort (age: 59.7 ± 8.4, BMI: 31.6 ± 7.2 (mean±SD)). After filtering, sixteen features (time and frequency domain) were extracted from each signal using a sliding window of ten seconds with eight seconds overlap. Two models were developed based on bidirectional long short-term memory (bLSTM) neural networks: 1)a two-class model for classification of windows as “normal” or “event”, and 2)a four-class model for classification as “normal”, “obstructive”, “central”, or “mixed”. 1882 subjects were used for training; 249 subjects were used for validation. Preliminary results were obtained for a test set of 235 subjects.

Results:
With respect to the total number of events, the two-class model obtained precision of 0.740 and recall of 0.769. The four-class model obtained precision of 0.787, 0.205, and 0.100, and recall of 0.685, 0.190, and 0.0985, for obstructive, central, and mixed events, respectively. The Pearson correlation coefficient between annotated and predicted apnea hypopnea index (AHI) were 0.844 and 0.861 for the two-class and the four-class model, respectively.

Conclusion:
These results indicate that obstructive events can be reliably detected with a bLSTM network. However, the models had difficulties detecting central and mixed events correctly, which were present in a very limited number (1.5 % and 0.21 % of events). Future work includes improving the models for central and mixed event detection.