02 Issue | 01 Volume | February 2022

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NEWS BEADS

COPD **focus**

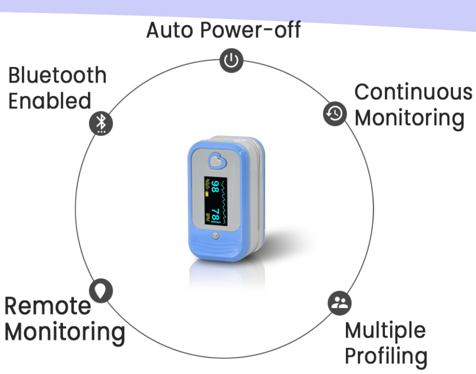
- Continuous vital monitoring
- Machine Learning
- Classification of COPD and factors prognosticating

ADDRESSING THE NEEDS OF INTEGRATION OF MACHINE LEARNING WITH VITAL MONITORING IN COPD MANAGEMENT

Tailored support is needed for patients with COPD to improve overall quality of life. The quest for vital parameter monitoring among COPD for predicting acute exacerbations could possible also include a factor evaluating the respiratory viral infection.

Use of continuous Vital monitoring in COPD

Continuous vital monitoring among patients with COPD offers unique insight into the interactions between physiology, behavior and symptoms. It can detect the exacerbations at the earliest and possible intervention. Vital parameters include heart rate (HR), respiratory rate (RR), temperature and peripheral oxygen saturation (SPo2). Can the variations in these parameters predict an impending acute attack symptomatic exacerbation in patients with COPD? Are there any specific parameters or events that are specific to COPD exacerbations? In this newsletter we examine the possible answers. The prevalent global pandemic of COVID19 has complicated the management of every disease particularly the respiratory illness. COPD is an independent risk factor resulting in mortality among COVID patients and the effects cannot be undermined.[1,2] Contrary to the general assumption, during January 2020 to May 2021, there was 50% reduction in hospitalization for COPD exacerbations as suggested by meta-analysis of 13 studies evaluating the COPD situation.[3]



Oxy2 supreme

Our continuous remote monitoring solution offers earlier detection of acute events of COPD. Coupled with lifestyle and location tracking IoTs, it is possible to predict an acute event based on machine learning algorithms. Personalized and adaptive BODE index computations coupled with continuous vital monitoring provide required K means and hierarchical clusters to classify COPD and to predict an acute exacerbation.

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Machine learning in COPD Management

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> “Maching learning mortality prediction is outperforming traditional models in predicting the acute exacerbations of COPD. In this regard, continuous vital monitoring devices significantly contribute to the overall well-being of the COPD by providing early indications of worsening of COPD status.

Using k-means and hierarchical clustering (two of the important machine learning methods), COPD can be classified into four clusters.

Cluster 1
- Putative asthma-COPD overlap
- Highest risk of acute exacerbation

Cluster 2
- Mild COPD

Cluster 3
- Moderate COPD

Cluster 4
- Severe COPD
- highest COPD assessment test score

This significant reduction in cases indicate a possible respiratory viral infections triggering the acute events in COPD patients. So, the quest for vital parameter monitoring among COPD for predicting acute exacerbations could possible also include a factor evaluating the respiratory viral infection.

Tailored support is needed for patients with COPD to improve overall quality of life.[4] Though efforts in bringing supported self-management of COPD were not promising earlier,[5,6] a Cochrane review suggested that assisted self-management improves health-related quality of life.[7] Therefore, efforts in assisting patients for predicting, prognosticating, managing and preventing acute exacerbations using present day artificial intelligence and machine learning will be beneficial to the patients.[8,9]

As the latest report indicate exertional desaturation has higher mortality than non-desaturation in COPD,[10] a vital monitoring system in place for detection of acute exacerbations must include a oxygen saturation. Other parameters that are widely used to predict the mortality among COPD are body mass index (B), airflow obstruction (O), dyspnea (D) and exercise capacity (E) - BODE index. Similarly, there are other indices - DOSE index (dyspnea, airflow obstruction, smoking status and exacerbation frequency),[11] ADO index (age, dyspnea and airflow obstruction),[12] SAFE index (St. George’s respiratory questionnaire score, airflow limitation and exercise tolerance).[13] Machine learning mortality prediction (MLMP) in COPD model can outperform all these existing traditional models to predict the mortality.[8]

FIVE PHENOTYPES INFLUENCING COPD OUTCOMES

1. Anxiety and depression
2. Severe airflow limitation and weakness,
3. Cardiovascular disease and diabetes
4. Obesity
5. Atopy and non-comorbidity

Main inputs for the machine learning experiments in COPD

Category	Input features
Screening and Diagnosis	Transcriptomic data[15]
	Serum metabolic biomarkers
	Clinical (lung sound)[16]
	COPD assessment test (CAT) score[17]
	spirometry features[16]
Management and Monitoring	Post-bronchodilator (BD) FEV1 % predicted[18]
	Diffusing capacity of carbon monoxide % predicted[18]
	Thoracic computed tomography[19]

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