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Machine Learning For Respiratory Disease Diagnosis And Monitoring: A Survey Of Recent Advances

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Abstract

Respiratory diseases, such as asthma and chronic obstructive pulmonary disease (COPD), are a major global health concern, affecting millions of people worldwide. Traditional methods for diagnosing and monitoring respiratory conditions often rely on invasive procedures, such as spirometry, which can be inconvenient and uncomfortable for patients. In recent years, there has been a growing interest in developing non-invasive and user-friendly methods for respiratory disease diagnosis and monitoring. Machine learning (ML) has emerged as a powerful tool for analyzing large amounts of data and identifying patterns that can be used to predict and classify respiratory conditions. ML algorithms have been successfully applied to a variety of tasks in respiratory medicine, including asthma risk prediction, classification of respiratory sounds, and automatic detection of respiratory events. In this review paper, the recent advance in ML-based methods for respiratory disease diagnosis and monitoring is discussed. The papers of Asthma risk prediction, Classification of respiratory sounds and Automatic detection of respiratory events are focused on. ML has the potential to make a significant contribution to the fight against respiratory diseases. By developing and deploying ML-based methods for respiratory disease diagnosis and monitoring, the quality of care for patients with these conditions has improved and improves the burden of respiratory diseases on healthcare systems.

SECTION I

Introduction

Respiratory illnesses, such as asthma and chronic obstructive pulmonary disease (COPD), are a major global health problem that impact millions of individuals throughout the world. These disorders can result in severe morbidity and death, as well as a major strain on healthcare systems. Traditional methods of diagnosing and monitoring respiratory disorders sometimes rely on intrusive techniques such as spirometry, which can be difficult and unpleasant for patients. In recent years, there has been a surge in interest in creating non-invasive and user-friendly approaches for diagnosing and monitoring respiratory diseases.

Machine learning (ML) has been developed as an effective method for analyzing vast volumes of data and detecting patterns that may be used to forecast and categories respiratory illnesses. ML algorithms have been effectively used for a number of respiratory medical applications, including asthma risk prediction, respiratory sound categorization, and automated detection of respiratory events.

This review paper describes recent improvements in ML-based approaches for respiratory illness diagnosis, monitoring and using Assist devices for curing

- Asthma risk prediction: Machine learning algorithms have been used to create predictive models that can identify those who are at high risk of acquiring asthma. These models can be used to influence methods for early intervention and prevention.
- Classification of respiratory sounds: ML algorithms have been used to categories respiratory sounds into normal, asthmatic, and COPD categories. This can be used to diagnose and monitor respiratory diseases in a non-invasive manner.
- Automatic identification of respiratory events: ML algorithms have been used to automatically recognize respiratory events from audio recordings, such as coughs and snores. This technology may be utilized to create real-time respiratory monitoring systems.

Additionally this paper covers the different ways of diagnosing, monitoring and using Assist devices for curing of different respiratory disorders.

SECTION II

Related Work

Gautam S Bhat, et,al (2021), provided a machine learning (ML)-based asthma risk prediction tool. Simple particulate matter (PM) and weather data are used to forecast Peak Expiratory Flow Rates (PEFR) value. The suggested method's performance is improved utilizing objective assessments. The low-cost gadget consists of an edge device, sensors, and an IoT platform. The complete tool is implemented on a Smartphone as an m-health application, utilizing various IoT resources. Individual patients' asthma risk can be successfully predicted using the technique.[1]

Dohyeong Kim, et,al (2019), they provided a machine learning (ML)-based asthma risk prediction tool. The complete tool is implemented on a Smartphone as a mobile-health (m-health) application, utilizing Internet-of-Things (IoT) resources. Peak Expiratory Flow Rates (PEFR) are well-known asthma risk predictors and are often monitored using external tools such as peak flow meters. In this study, they discovered a link between particulate matter (PM) detected indoors and the outdoor weather and the PEFR. In comparison to the best peak flow value recorded by each individual, the PEFR results are divided into three categories: 'Green' (Safe), 'Yellow' (Moderate Risk), and 'Red' (High Risk). The CNN architecture is utilized to map the link between the indoor PM and meteorological data and the PEFR readings. In terms of root mean square and mean absolute error accuracy measurements, the suggested method is compared to state-of-the-art deep neural network (DNN)-based techniques. These performance measurements are superior to other approaches reported in the literature for the proposed method. The complete arrangement is run as an app on a Smartphone. The input data is collected using an IoT system that includes a Raspberry Pi. This aid can be a cost-effective technique for predicting the likelihood of asthma attacks.[3]

Md. Ariful Islam, et,al (2018), their study explains that Lung sounds contain important information about the pathophysiology of the lungs. The combination of modern digital signal processing methods and a machine learning framework offers enormous promise for exploiting lung sound signals to assess lung health. In this work, they identified normal, asthmatic, and COPD participants using posterior lung sound waves, which had previously been unexplored. Asthma and COPD have similar characteristics, making categorization of both disorders on a single platform difficult. Using a unique 4-channel data collecting method, they gathered lung sound signals from 60 participants (20 normal, 20 asthmatic, and 20 COPD). A feature extraction strategy is provided for extracting features from the power spectral density (PSD) sub-bands and feeding them to the artificial neural network (ANN) classifier for 3-class classification. Changes in the posterior lung sound signals are targeted for feature extraction, which is independent of wheeze or any other marker. When the information from all four channels is used combined, the proposed multichannel-based multiclass classification system achieves respectable classification accuracy that is substantially greater than the theoretical and empirical chance values.[2]

Viswam Nathan, et,al (2019), their study explains that Chronic pulmonary illness is a primary cause of death in the United States. Continuous passive monitoring of people using mobile sensors can aid in the detection of disease, the estimation of severity, the tracking of progression across time, and the prediction of unfavorable exacerbation events. Analysis of passively recorded natural speech patterns is one of the most convenient ways to achieve this aim. Asthma and chronic obstructive pulmonary disease (COPD) have been linked to changes in pause patterns and prosodic aspects of speech. Experiments were carried out on a group of 131 people, 91 of whom had asthma or COPD and 40 of whom were healthy controls. Patients and healthy people were distinguished with 68% accuracy; moreover, the subset of patients with the most severe illness severity was identified with 89% accuracy.[4]

Ebrahim Nemati, et,al (2020), their study explains that gold standard for the diagnosis and monitoring of chronic pulmonary illnesses is the spirometry test, which measures the patient's lung function. Spirometry is currently performed in hospital settings by having patients aggressively blow air out of their lungs and into the spirometer's tubes while under the observation and continual instruction of professionals. This test is costly, time-consuming, and not easily relevant to the everyday monitoring of these patients. When coughing, the lung mechanism is quite similar to when a spirometry test is performed. This consists of a deep inhale, compression of the air, and a strong exhale. As a result, it is fair to expect that blockage of lung airways will have a comparable influence on cough characteristics as well as spirometry measurements. This paper investigates the estimation of lung obstruction using cough acoustic features. In a clinical setting, a smartphone microphone and a hospital-grade spirometry lab were used to collect 3695 coughs from patients with four different conditions and four different severity categories, as well as their lung function measurements. The lung obstruction was estimated with an MAE (Mean Absolute Error) of 8% for COPD and 9% for asthma populations after feature-set optimization and model hyper parameter tuning. In addition to estimating lung obstruction, they were able to accurately classify patients' disease states and severity within each disease state with 95% accuracy.[5]

A.Raji, et,al (2016), their study explains that people nowadays suffer from respiratory issues. The illnesses encompass a variety of conditions such as sleep apnea, chronic obstructive pulmonary disease, and asthma. These disorders are the leading cause of hospitalization in the elderly. Patients with chronic illnesses must monitor their vital signs on a regular basis. The vital signs are the fundamental measures of the body's functioning. Heart rate, temperature, blood pressure, respiratory rate, oxygen saturation, and blood glucose level are among vital signals in our body. The respiration rate monitor is one of the most critical vital indicators for patients in the Intensive Care Unit (ICU). The respiratory rate is determined using an LM35 temperature sensor, and the patient's respiration is continually monitored using the voltage values of breathed and exhaled air. The NRF24l01 is used to send sensor data from the house to the medical centre.

The data is then broadcast via a website over Ethernet to determine the patient's state, which is valuable to the doctor. The data is also shown on a Liquid Crystal Display (LCD). When the threshold is achieved, an alert is created, as well as a notification on a webpage. As a result, doctors or medical experts are aware of the patient's situation as soon as possible. People who use data mining techniques may be able to learn about their health without the assistance of medical specialists.[6]

Ipek Sen, et,al (2021), their study explains that because of overlapping symptoms, asthma and chronic obstructive pulmonary disease (COPD) might be misdiagnosed. The goal of this work is to provide a technique for differential diagnosis of the two illnesses based on multivariate pulmonary sound analysis. The 14-channel pulmonary sound data are theoretically modeled with a multivariate (or vector) autoregressive (VAR) model, and the model parameters are supplied into the classifier. Separate classifiers are assumed for each of the flow cycle's six sub-phases, namely, early/mid/late inspiration and expiration, and the six judgments are combined to arrive at the final conclusion. The parameter classification is done in a Bayesian framework with the likelihoods assumed to be Gaussian mixture models (GMM), and the six sub-phase judgments are merged by voting, with the weights acquired using a linear support vector machine (SVM) classifier. The trial includes fifty participants, 30 of whom have asthma and 20 of whom have COPD. The classifier's greatest accuracy is 98 percent, which corresponds to proper categorization rates of 100 and 95 percent for asthma and COPD, respectively. The most noticeable sub-phase for distinguishing between the two disorders is mid-inspiration. The technique shows promise in terms of asthma-COPD distinction using acoustic data. The findings also show that the six sub-phases are not equally important in differentiation. In the absence of adequate spirometric testing, pulmonary sounds analysis may be a useful adjunct in clinical practice for differential diagnosis of asthma and COPD.[7]

Tasnuba Siddiqui et,al (2018), their work explains that Chronic obstructive pulmonary disease (COPD) and asthma are both long-term lung illnesses. Disease monitoring with low-cost, high-efficiency sensors can make disease control simple and practical for patients. They offer a model for illness severity evaluation utilizing wearables and mobile health applications that uses just heart rate and SpO2 (from a pulse Oximeter sensor). The MIMIC III Waveform Database Matched Subset was used to acquire patient data. There are 158 people in the dataset. The suggested method analyses both the heart rate and the SpO2 signal of patients to classify the severity of the disorders. A rule-based threshold technique in real-time evaluation is being strategically investigated for the categorization system. Furthermore, based on the estimated metrics, a strategy for judging severity as an Event of Interest (EOI) is provided. This sort of autonomous system for real-time evaluation of patient state has the potential to enhance individual health through continuous monitoring and self-management, as well as the overall Smart and Connected Community (SCC) health status.[8]

Sudip Vhaduri et,al (2019), proposed that their preliminary findings show that smart-phone-based automated cough and snoring monitors can be used to analyze the progression of various respiratory disorders as well as to monitor sleep quality.[9]

Qian wang, et,al (2020), proposed that they offer a technique for the diagnosis of COPD based on transfer learning, i.e., the BPD algorithm, for the prediction of few-shot learning in COPD investigations. To produce instances close to the target domain, BPD first use instance-based cascaded transfer learning. The cross-domain feature filtering approach is then used to extract the co-occurrence characteristics of source and target domains. Learning is transferred from a multi-disease source domain to the COPD domain using instances and co-occurrence characteristics to build the target domain classification model. Following that, an elastic network is employed to increase the model's generalization performance even more. The BPD technique combines instance-based transfer with feature-based transfer, and their numerous trials show that it can produce reliable prediction results. Their results further suggest that the BPD technique not only improves COPD detection but can also successfully differentiate between various illnesses with comparable symptoms. They intend to use several diagnostic approaches in future studies to mimic medical diagnostic thinking in order to construct more accurate and interpretable sickness prediction models.[10]

Abubakar Abid, et,al (2017), they explain the partial pressure of carbon dioxide in exhaled breath using a single-alveolar-compartment model as measured by time-based capnography. This model is used to estimate respiratory parameters, which are subsequently linked to the clinical condition of patients with obstructive lung disease. Using acceptable assumptions, they construct an analytical solution to the model that describes the capnogram's exhalation segment. This solution is parameterized by alveolar CO2 concentration, dead-space fraction, and exhalation time constant. Individual capnogram data is used to estimate these amounts on a breath-by-breath basis. The model is used to analyze datasets from participants with normal (n=22) and chronic obstructive pulmonary disease (COPD) (n=24), as well as patients undergoing methacholine challenge testing for asthma (n=22). A classifier trained on data from 5 normal and 5 COPD subjects and based on linear discriminant analysis in logarithmic coordinates, using estimated dead-space fraction and exhalation time-constant as features, produced an area under the receiver operating characteristic curve (AUC) of 0.99 in classifying the remaining 36 subjects as normal or COPD. With 50 replicates, the 95% confidence interval of AUCs ranged from 0.96 to 1.00. Qualitatively substantial patterns in parameter alterations were detected in patients undergoing methacholine challenge testing. A simple mechanistic model that estimates underlying respiratory parameters from the capnogram can be used to diagnose and monitor chronic and reversible obstructive pulmonary disease.[11]

Adam Rao, et,al (2018), proposed that New tactics for measuring and interpreting lung acoustic signals that originate internally, such as breathing or voice sounds, or are introduced externally, such as in chest percussion or airway insonification, have been enabled by recent advances in sensor technology and computer analytic methodologies. A greater knowledge of these sounds has led to the development of new technology that allows for extremely precise as well as portable measurement alternatives in the hospital, clinic, and even at home. This covers sonic stimulation and lung measuring instruments. They begin by reviewing the foundations of acoustic lung signals as well as the pathophysiology of the illnesses detected by these signals. Then, they will look at several techniques of monitoring and producing signals that have been employed in recent studies to diagnose lung diseases. These novel methods, when paired with signal processing and modelling techniques, reduce noise and enable better feature extraction and signal categorization. Finally, they said the findings of human subject investigations that used both hardware and signal processing technologies to reliably detect common lung illnesses. This study highlights current research topics in contemporary lung acoustics and supports standardization of future work in this field.[12]

Sahar Ahmadzadeh, et,al (2020), proposed that this study gives an in-depth examination of various methods for measuring critical physiology factors that induce sleep disordered breathing (SDB). SDB is a chronic condition that can cause a variety of health issues, including high blood pressure and even a heart attack. As a result, detecting SDB at an early stage is critical. Measuring is an important first step before diagnosing. SBD-related vital health indicators may be tested using invasive or non-invasive procedures. With the ageing population, improvements in home health management systems are more essential now than even a decade ago. Furthermore, typical health parameter measuring procedures such as polysomnography are inconvenient and incur additional expenditures for users. As a result, electronics and communication science are merged in current sophisticated self-health management systems to produce appliances that may be utilised for SDB diagnosis by monitoring a patient's physiological data with greater comfort and accuracy. Furthermore, advancements in machine learning algorithms enable precise means of evaluating measured data. To diagnose SDB, this study includes a complete analysis of measuring methodologies, data transfer, and communication networks, as well as machine learning algorithms for sleep stage categorization.[63]

Ali Azarbarzin, et,al (2011), proposed that an automated and unsupervised snoring detection technique is proposed in this study. Two microphones were used to record the respiratory sound signals of 30 individuals with varying degrees of airway obstruction: one positioned over the trachea (the tracheal microphone) and the other freestanding (the ambient microphone). All of the recordings were made while sleeping with full-night polysomnography. The vertical box (V-Box) technique was used to identify the sound activity events. To extract discriminative characteristics from sound events, the 500-Hz subband energy distribution and principal component analysis were applied. The sound events were then labelled as snoring or no-snore using an unsupervised fuzzy C-means clustering approach, which might be breath sound, swallowing sound, or any other noise. Manual annotation of sound signals was used to test the algorithm. The suggested algorithm's overall accuracy was determined to be 98.6% for tracheal sounds recordings and 93.1% for ambient microphone sounds.[13]

Surajit Bagchi, et,al (2017), proposed that there is a global need to develop noninvasive, simple, quick, selective, affordable, and portable illness evaluation tools. When compared to standard analytical procedures, enzyme-based bio-sensing systems offer all of these potential advantages. This paper proposes a carbonic anhydrase enzyme (CA) (E.C. 4.2.1.1) based cost-effective, highly selective, and reproducible CO_2 biosensing system that can accurately measure CO_2 concentration (ppm level) in expired breath to provide valuable information for assessing the subjects' respiratory disorders. CA is isolated from spinach leaves and immobilised on an electrode assembly. When the assembly comes into touch with aqueous CO_2, it creates a detectable electrical signal (mV). The sensor has a linear response from 160 ppm to 2677 ppm of CO_2 concentration dissolved in water, good sensitivity (0.132mV/ppm), and a rapid reaction time of 12 seconds. Repeatability, shelf life (5 months), re-usability (20 times), and selective reactivity to CO_2 molecules in exhaled breath are among the attributes. The biosensor's viability in a proper set-up for home-based monitoring of CO_2 in exhaled breath has been presented and justified. The technology demonstrated a strong correlation between sensor findings and recognized clinical tests.[14]

Vivekananthan Balakrishnan, et,al (2019), proposed that the measurement of respiratory rate (RR) is becoming increasingly used for monitoring the evolution of clinical events such as cardiac arrest or admission to the intensive care unit (ICU). Current methods of respiration monitoring are difficult, intrusive, and expensive, necessitating the use of alternative procedures. In this study, they used wearable and flexible technology to create humidity sensors for long-term continuous respiration monitoring. The sensors were created using manual sketching and printing procedures, with graphite trace and silver nanoparticles as two separate sensing materials. Scanning Electron Microscope (SEM) was used to characterise the surface morphologies of the devices in order to illustrate the construction of the sensors. In order to get the Raman Spectra, the material was also characterised. Because of its biodegradability, porosity, and disposability, paper was chosen as a flexible substrate. The humidity sensing properties of the sensors revealed that the Graphite on Paper (GOP) sensor had the highest sensitivity of 0.0564%. Furthermore, the paper's hygroscopic characteristic allows for the conversion of humidity changes during inhaling and exhale into electrical impulses. The electrical impulses are transferred to a computer via an interface using a basic data recording setup. These signals might readily distinguish between normal, deep, and apneic breathing situations, as well as information on respiration rate and pattern. Sensor functioning was also examined during mild and strenuous workouts. The suggested sensor combines the benefits of being low cost, non-invasive, very sensitive, stable, and has enormous promise for wearable/flexible healthcare technologies.[15]

Xue, et,al (2019), proposed that Respiratory sound can be used to differentiate sleep stages and provide a non-contact and cost-effective method of diagnosing and monitoring sleep-related illnesses. While most existing respiratory sound-based techniques concentrate on a small number of sleep phases, such as Sleep/Wake and Wake/REM (Rapid Eye Movement)/NREM (Non-REM), recognising sleep stages at a finer level is crucial for assessing sleep quality. They study a sleep stage identification technique based on respiratory sound for the first time to categorise sleep states into four sleep stages: awake, REM, light sleep, and deep sleep. Nonlinear characteristics of snoring sound, as well as time-domain elements of respiratory sound, are proposed to further define snoring-related respiratory sound signals. To successfully fuse the three sets of features for discriminative feature selection, a novel feature fusion strategy integrating generalised canonical correlation analysis (CCA) with the ReliefF algorithm is proposed. Decision Tree, Support Vector Machines (SVM), KNearest Neighbour (KNN), and the ensemble classifier are popular classifiers for final stage identification. To put thier proposed technique to the test, they built an in-house dataset of 13 nights of sleep audio recordings from a sleep laboratory. Experiment results reveal that their proposed strategy outperforms comparable existing methods and has potential for large-scale non-contact sleep monitoring.[16]

Carlo Massaroni, et,al (2019), proposed that Wearable devices are gaining popularity in applications involving the monitoring of physiological data. Piezoresistive strain sensors are an excellent choice for developing wearables for a variety of medical applications. Respiratory monitoring, for example, can be accomplished by tracking chest movements. The goals of this work are threefold: (i) the experimental evaluation of elastic piezoresistive textile; (ii) the effect of length and breadth on piezoresistive response; and (iii) the application of these elements to the development of a smart textile (ST) for respiratory monitoring. The ST is made up of six piezoresistive components. To evaluate the properties of the piezoresistive components, static calibration and hysteresis analysis were performed. The ST's practicality for respiratory monitoring was evaluated on four healthy volunteers under two situations (silent breathing and tachypnea). The ST computed respiratory frequency values and compared them to those obtained by a reference system (i.e., a motion capture system). The length and breadth of the piezoresistive element affect its sensitivity and hysteresis. In terms of ST performance, there was good agreement with data supplied by the reference system. Indeed, when the output of single sensing components and their total were considered, the difference in average respiratory frequency was consistently less than 1% and 4% during silent breathing and tachypnea, respectively. The suggested ST appears to be appropriate for respiratory frequency monitoring in a wide range of values where unobtrusiveness is important.[17]

Broto Chakrabarty, et,al (2021), proposed that the severe acute respiratory syndrome coronavirus 2 (SARS CoV-2) causes COVID-19, a highly infectious illness. Patients above the age of 65, as well as those with diabetes, cancer, or cardiovascular disease, had a much higher case fatality rate. Human proteins angiotensin-converting enzyme 2 (ACE2), transmembrane protease serine 2 (TMPRSS2), and basigin (BSG) interact with SARS-CoV-2 proteins with high confidence. They used these three proteins as seed nodes and used the random walk with restart approach to build a protein protein interaction sub-network that reflects the impact of viral invasion on the human interactome. 'Insulin resistance,' 'AGE-RAGE signalling in diabetic complications,' and 'adipocytokine signalling' were discovered to be shared pathways connected with diabetes, cancer, and cardiovascular problems. The link between these essential pathways and ageing and its associated disorders reveals the biological foundation of COVID-19 mortality. Based on gene expression investigations, they found medicines that affect these proteins/pathways. They concentrated on medications that strongly inhibit ACE2 as well as other key proteins discovered by the network-based method. COL-3 had previously demonstrated action against acute lung damage and acute respiratory distress, whereas entinostat and mocetinostat have been studied for non-small-cell lung cancer. These medications, they believe, can be repurposed for COVID-19.[18]

Chandan Karmakar, et,al (2014), proposed that Respiratory events during sleep cause cortical arousals and alterations in autonomic indicators in sleep disorder breathing (SDB). Finger photoplethysmography (PPG) has been found to be a reliable means of measuring sympathetic activity. They hypothesise that variations in PPG signals are adequate to anticipate the occurrence of respiratory-event-related cerebral arousal. In this work, They use PPG characteristics to create a respiratory arousal detection model in SDB participants. This study examined PPG signals from ten SDB participants (9 male, 1 female) ranging in age from 43 to 75 years. Time domain characteristics of PPG signals, such as 1) PWA—pulse wave amplitude, 2) PPI—peak-to-peak interval, and 3) Area—area under peak, were employed to detect arousal moments. In this investigation, PWA and Area performed better (greater accuracy and lower false rate) than PPI characteristics. After exploring various groups of these variables, it was shown that combining PWA and Area (PWA + Area) provided superior accuracy with a reduced false detection rate in arousal detection. PPG-based arousal indices agreed well over a wide variety of decision thresholds, resulting in an area under the curve of 0.91 for the receiver operating characteristic. The final studies' decision threshold (PCthresh = 25%) yielded a sensitivity of 68.1% and a specificity of 95.2%. At PCthresh = 25% or PPI, PWA, Area, and PWA + Area features, the accuracy was 84.68%, 85.15%, 86.93%, and 50.79%, with a false rate of 21.80%, 55.41%, 64.78%, and 50.79%, respectively. This implies that integrating PWA and Area characteristics lowered the false positive rate while having no effect on the arousal detection system's sensitivity. Finally, the PPG-based respiratory arousal detection model provides a simple and promising alternative to the traditional EEG-based respiratory arousal detection method.[19]

Guo dan, et,al (2018), proposed that a novel angular velocity-based human respiration detection approach for continuous recording and analysis of respiratory data is suggested. By relying on pre-defined basic methods and patient-specific information received from a wearable sensor, thier suggested system is capable of monitoring human breathing and assisting in the identification of suspected respiratory illnesses. In order to capture a synchronous signal, their signal verification platform is outfitted with a carbon dioxide concentration measuring equipment. In addition, the respiratory waveform is extracted from the original data using a median filter approach. The resulting human respiration angular velocity waveform is then compared to the respiratory carbon dioxide concentration waveform, and the correctness of their selected parameters is confirmed. The test findings show that their constructed system is suitable for unobtrusive respiratory signal capture and processing; hence, it can be regarded a feasible alternative for physiological monitoring and screening for respiratory illnesses.[20]

Bhagya D, et,al (2020), proposed that the concentration of carbon dioxide (CO2) in exhaled breath can give non-invasive and continuous information about an individual's metabolic and respiratory functions. An acoustic virial equation has been used to calculate the content of carbon dioxide in exhaled air using a capnographic sensor based on sound velocity. The recovered capnographic signal is then used to identify cardiopulmonary diseases such as COPD and CHF. The suggested sensor's capnographic signal correlates well with the signal from a conventional sensor, having a squared correlation value of 0.8732. For Healthy/COPD, Healthy/CHF, and COPD/CHF categorization instances, they attained accuracy of 91.3%, 87.76%, and 88.82%, respectively. The performance shows that the suggested approach is suitable for use as a diagnostic instrument for cardio-respiratory disorders.[21]

J. Di Tocco, et,al (2020), proposed that Workers that are stressed may have low motivation, poor concentration, and physical issues, which can contribute to workplace accidents. Respiratory frequency (fR) is regarded as one of the most dependable markers of workers' mental load and exhaustion condition. Monitoring this parameter with wearable devices is an efficient way to maintain Occupational Health and Safety. They created an innovative wearable device with flexible sensors based on fibre Bragg gratings (FBGs) to monitor fR in static and dynamic occupational environments. This article describes the system as well as the metrological properties of the flexible sensors in terms of responsiveness to strain and temperature changes, as well as hysteresis error. The device's performance is also described, having been examined in a laboratory during the execution of tasks simulating real-world work activity. The positive results motivate the development of the system for use in real-world workplaces to collect quantitative data on workers' psychophysical condition and its relationship to stress level.[22]

Dou Fan, Aifeng Ren, et,al (2019), proposed that Non-invasive respiration detection technologies are extremely useful in healthcare applications and illness diagnosis because they reduce the physical strain on the patient and reduce the need for active participation from the subject. This technology eliminates the need for additional preparations, decreases environmental limitations, and improves the ability of real-time respiratory detection. Identifying aberrant breathing patterns in real time is also required for the diagnosis and monitoring of potential respiratory illnesses. A non-invasive approach for recognising numerous breathing patterns is provided, which is utilised to identify diverse breathing patterns as well as extract respiratory rate. They first assess the feasibility of using this non-contact approach to measure various breathing patterns. Then, using a C-band sensing approach in an indoor setting, they discover multiple aberrant breathing patterns associated with various respiratory illnesses in real time. The correlation between C-band sensing technology and touch respiratory sensor is evaluated using mean square error (MSE) and correlation coefficient (CC). The findings reveal that all MSE are less than 0.6 and all CC are greater than 0.8, indicating a significant correlation between the two variables utilised to detect each breathing pattern. Clinical Implications: The C-band sensing technique is utilised not only to detect respiration rates but also to identify breathing patterns, and it is regarded as a preferred noncontact alternative approach to standard contact sensing methods. The C-band sensing technology can also be used to diagnose some respiratory illnesses non-invasively.[23]

Atena Roshan Fekr, et,al (2015), proposed that a reliable long-term monitoring and identification of breath problems at an early stage improves medical act, life expectancy, and quality of life while lowering treatment and medical service costs. As a result, in medical applications, real-time unobtrusive monitoring of respiratory patterns and breath parameters is crucial. They propose an intelligent system for patient home care that can measure respiratory rate and tidal volume variations using wearable sensor technologies in this research. The suggested method is intended primarily for diagnosis and treatment of individuals with abnormal breathing, such as respiratory problems following surgery or sleep disorders. Wearable calibrated accelerometer sensor, Bluetooth Low Energy (BLE), and cloud database composed the entire system. The trials were carried out with 8 people, and the total error in respiration rate computation was 0.29%0.33% when the SPR-BTA spirometer was used as a reference. They also present a method for estimating Tidal Volume Variability (TVvar) that is verified using Pearson correlation. Furthermore, because it is vital to detect critical events caused by a fast spike or decrease in the patients' per breath tidal volume, they present a way to automatically discover the proper threshold values based on each unique breath characteristics. As a result, the system can identify substantial changes with greater than 98% accuracy and give timely feedback such as a sound warning for round-the-clock respiratory monitoring.[24]

Atena Roshan Fekr, et,al (2016), proposed that Respiratory illness is a common ailment that is linked to a variety of negative health outcomes. Because present diagnostic methods are intrusive and unsuitable for real-time m health applications, they investigate a simple and low-cost automated technique based on wearable MEMS sensor technology. The suggested system employs motion sensors to detect variations in the anterior-posterior diameter of the chest wall during breathing function, as well as to extract useful respiratory properties for use in the categorization of breathing problems. Extensive assessments of six well-known classifiers using unique feature extraction approaches to discriminate between eight distinct abnormal breathing patterns are offered. The impact of sensor number, sensor location, and feature selection on classification performance are examined. The experimental findings with ten individuals reveal that Support Vector Machine (SVM) and Decision Tree Bagging (DTB) have the best accuracy rates of 97.50% and 97.37%, respectively, with all features and after feature selection. A binary classification is also proposed to distinguish between healthy persons and those with breathing issues. The accuracy, sensitivity, specificity, F1-score, and Mathew Correlation Coefficient (MCC) are all used to measure classification characteristics. The accuracy rates above 98% indicate that DTB performs well in binary recognition, which is corroborated by the proposed new features.[25]

Maziar hafezi, et,al (2020), proposed that a Sleep apnea is a chronic respiratory disease that needs a full night of in-laboratory polysomnography (PSG). PSG, on the other hand, is costly, time-consuming, and inconvenient. As a result, there is a need for more comfortable wearable devices to monitor sleep apnea. The goal of this work was to use deep learning algorithms to assess the severity of sleep apnea based on breathing movements that may be readily captured across the trachea. Adults sent to the sleep laboratory at the Toronto Rehabilitation Institute for overnight sleep investigations (N=69) were included in the study. An accelerometer was placed to the participant's suprasternal notch at the same time as the PSG to monitor tracheal breathing movements. Twenty-one tracheal movement characteristics were retrieved and employed in a deep learning classifier to detect respiratory events. The number of times per hour of sleep was used to calculate the apnea hypopnea index (AHI). The F1 score of the event-by-event identification method ranged from 12% to 71% for various groups of sleep apnea severity. The calculated and PSG-derived AHI had a good correlation (r=0.86, p0.0001). The sensitivity, specificity, and accuracy of diagnosing sleep apnea using the AHI cut-off of 15 were 81%, 87%, and 84%, respectively. Advanced machine learning techniques combined with respiratory-related motions can reliably measure sleep apnea severity and identify respiratory events while sleeping. The suggested technology has the potential to be adopted as a low-cost and dependable wearable device for monitoring sleep apnea in the home and community.[26]

T. Noah Hutson, et,al (2020), proposed that the major cause of epilepsy-related mortality is sudden unexpected death in epilepsy (SUDEP), and its pathophysiological underpinnings are unclear. They set out to record and analyse simultaneous electroencephalographic (EEG), electrocardiographic (ECG), and unrestrained whole-body plethysmographic (Pleth) signals from control (WT - wild type) and SUDEP-prone mice (KO - knockout Kcna1 animal model) signals for the first time. Using multivariate autoregressive models (MVAR), they assessed all tri-organ effective directional interactions in the frequency domain across time (hours) using the generalised partial directed coherence (GPDC). SUDEP-prone (KO) animals had (p 0.001) reduced afferent and efferent interactions between the heart and the brain across the entire frequency spectrum (0-200Hz), enhanced efferent interactions from the brain to the lungs and from the heart to the lungs at high (>90 Hz) frequencies (especially during seizure activity), and decreased feedback from the lungs to the brain at low (40 Hz). These findings suggest that impairments in the afferent and efferent pathways of the holistic neuro-cardio-respiratory network may result in SUDEP, and that effective connectivity metrics and their dynamics may serve as potential biomarkers of SUDEP and seizures, respectively.[27]

Katsufumi Inoue, et,al (2018), proposed that the goal of this study was to create a swallowing evaluation approach to aid in the prevention of aspiration pneumonia. The technology employs basic sensors to track a person's swallowing function throughout the day. The following are the important aspects of they suggested (1) They assess swallowing function using respiratory flow, laryngeal motion, and swallowing sound signals recorded by simple sensors; (2) They classify the recorded signals as belonging to healthy subjects or dysphagic patients; and (3) They analyse the recorded signals using both a feature extraction method (linear predictive coding) and a machine learning method (support vector machine). Based on the findings of their experiments with 140 healthy volunteers (54.5 32.5 years old) and 52 dysphagia patients (75.5 20.5 years old), their suggested approach could reach 82.4% sensitivity and 86.0% specificity. Despite the fact that 20% of testing sample sets were incorrectly identified, they believe that their proposed technique may aid in screening swallowing function exams. When combined with portable sensors, they suggested technique is suitable for non-invasive swallowing examination.[28]

Clara M. Ionescu, et,al (2014), proposed that the forced oscillation technique (FOT) is a lung function test that evaluates pulmonary impedance in clinical use. One of the primary benefits of FOT over other lung function tests is that it does not need the participant to do any particular breathing manoeuvres, making it one of the easiest tests to measure respiratory mechanics. The nonlinear effects in respiratory signals and related measuring instruments during FOT testing are described in this work. First, this article presents various enhancements made to a prototype FOT device to enable the creation of multisines at frequencies lower than 4 Hz. Second, two strategies for detecting nonlinear effects are evaluated: a robust method and a rapid way. The nonlinear distortions in a prototype FOT device and a commercial FOT device may be compared using these approaches. A new index concept is also used to quantify the nonlinear impacts. FOT lung function tests are done to gather two unique data sets: 1) a mixed group of asthma and cystic fibrosis patients and 2) a group of healthy volunteers. There is a considerable difference between the two groups in terms of the retrieved nonlinear contributions. This demonstrates that low frequency measures of respiratory mechanics may be used to evaluate lung diseases.[29]

Ireneusz Jabło´nski proposed that the Breathing is a fundamental physiological activity that is triggered and regulated by efferent neural system impulses. Improving their knowledge of the systems that underpin human breathing is of great importance. Another critical practical challenge is the development of noninvasive technologies for the diagnosis, prediction, and management of the respiratory system, which operates as a subsystem within the human organism's complicated physiological milieu and its external environment. This paper presents a succinct evaluation of a selected collection of recent strategies for exploring complicated and changing systems and time-series data sets. These approaches are based on a 1D entropic tool (approximate and sample entropy, abbreviated ApEn and SampEn), It is useful for examining the regularity and complexity of information included in data sets, as well as complex network theory, the recurrence plot (RP) technique, and the joint complex network-recurrence analysis mode. Real physiological data from individuals with central sleep apnea syndrome are used to get exemplary outcomes. Although ApEn and SampEn have been demonstrated to be sensitive approaches for detecting pathogenic causes altering breathing patterns during sleep, qualitative and quantitative research based on the RP strategy indicate even greater efficiency for this purpose. Furthermore, the second method of analysis allows for multi-dimensional correlation of available data, which is useful for exploring the couplings between various physiological subsystems.[30]

Kaiyin Zhu, et,al (2019), proposed that a reliable, accessible, and non-intrusive approach for recording respiratory and heart rate is critical for improving sleep apnea monitoring and diagnosis. In this study, 50 people were referred for clinical overnight polysomnography (PSG), and an algorithm based on motion analysis of infrared video records was verified. The method records the displacements of chosen feature points on each sleeping participant and extracts respiratory rate and heart rate using principal component analysis and independent component analysis, respectively. With an average root mean square error (RMSE) of 2.10 1.64 breaths per minute, the nighttime estimation was within 1 breath per minute of the PSG-derived respiratory rate from the respiratory inductive plethysmography signal. With a mean RMSE of 7.47 4.79 beats per minute, 77.97% 18.91% of the overnight estimate was within 5 beats per minute of the heart rate determined from the pulseoximetry signal from PSG. There was no significant difference in estimating the RMSE of each signal based on variations in body posture, sleep state, or quantity of body covered by blankets. This vision-based approach may be effective for non-contact nighttime monitoring of breathing rate. However, heart rate monitoring is currently less dependable and will require more effort to increase accuracy.[31]

Chandan Karmakar, et,al (2014), proposed that the Respiratory moments during sleep cause cerebral arousals and autonomic marker alterations in sleep disorder breathing (SDB). The use of finger photoplethysmography (PPG) to determine sympathetic activity has been proved to be a reliable approach. Changes in PPG signals, their hypothesis, are sufficient to anticipate the occurrence of respiratory-event-related cerebral arousal. In this work, they use PPG characteristics to construct a respiratory arousal detection model in SDB participants. In this investigation, PPG signals from ten SDB participants (9 male, 1 female) ranging in age from 43 to 75 years were employed. To detect arousal moments, time domain characteristics of PPG signals such as 1) PWA—pulse wave amplitude, 2) PPI—peak-to-peak interval, and 3) Area—area under peak were employed. In this investigation, PWA and Area performed better (greater accuracy and lower false rate) than PPI characteristics. After exploring various groups of these variables, it was shown that combining PWA and Area (PWA + Area) provided superior accuracy with a reduced false detection rate in arousal detection. PPG-based arousal indices agreed well over a wide variety of decision thresholds, resulting in an area under the curve of 0.91 for the receiver operating characteristic. The final studies' decision threshold (PCthresh = 25%) yielded a sensitivity of 68.1% and a specificity of 95.2%. At PCthresh = 25% or PPI, PWA, Area, and PWA + Area features, the accuracy was 84.68%, 85.15%, 86.93%, and 50.79%, with a false rate of 21.80%, 55.41%, 64.78%, and 50.79%. This demonstrates that integrating PWA and Area characteristics lowered the false positive rate without significantly impacting the sensitivity of the arousal detection algorithm. Finally, the PPG-based respiratory arousal detection model provides a simple and promising alternative to the traditional electroencephalogram (EEG)-based respiratory arousal detection method.[32]

Krishan L. Khatri, et,al (2017), proposed that the Chronic respiratory disorders, particularly asthma and Chronic Obstructive Pulmonary Disease (COPD), have a negative impact on people's life by restricting their activities in a variety of ways. Overcrowding in hospital emergency departments (EDs) owing to respiratory infections under specific weather and pollution conditions degrades medical treatment quality and even restricts its availability. Forecasting high demand days would be a beneficial tool for ED management so that they may take actions to increase the availability of medical treatment. In this paper, they developed an Artificial Neural Network (ANN)-based classifier that predicts Peak Event (Peak Demand Days) of patients with respiratory diseases, primarily asthma and COPD, visiting EDs in Dallas County, Texas, in the United States. Peak Event accuracy and recall were 77.1% and 78.0%, respectively, whereas Non-Peak Event precision and recall were 83.9% and 83.2%, respectively. The system's total accuracy is 81.0%.[33]

Henri Korkalainen, et,al (2019), proposed that the identification of sleep phases is critical in the diagnosis of sleep disorders, the most common of which is obstructive sleep apnea (OSA). Manual sleep stage scoring, on the other hand, is time-consuming, subjective, and expensive. To address this problem, they wanted to create an accurate deep learning system for automated sleep stage categorization and to investigate the influence of OSA severity on classification accuracy. A hybrid convolutional and long short-term memory neural network was developed using overnight polysomnographic recordings from a public dataset of healthy persons (Sleep-EDF, n=153) and a clinical dataset (n=891) of patients with probable OSA. The model achieved sleep staging accuracy of 83.7% (=0.77) with a single frontal EEG channel and 83.9% (=0.78) when augmented with EOG on the public dataset. With a single EEG channel and two channels (EEG+EOG), the model attained accuracies of 82.9% (=0.77) and 83.8% (=0.78), respectively, for the clinical dataset. The accuracy of sleep staging deteriorated as the severity of OSA increased. The single-channel accuracy varied from 84.5% (=0.79) for people without OSA to 76.5% (=0.68) for people with severe OSA. In conclusion, deep learning offers high-precision automated sleep staging for suspected OSA patients, with the accuracy decreasing as OSA severity increases. Furthermore, the accuracy obtained in the public dataset outperformed previously reported state-of-the-art approaches. Adding an EOG channel had no discernible effect on accuracy. The automated, single-channel-based sleep staging might make EEG recording straightforward, accurate, and cost-effectively integrated into diagnostic ambulatory recordings.[34]

Henri Korkalainen, et,al (2020), proposed that a Traditional sleep staging, which uses non-overlapping 30-second epochs, ignores repeated sleep-wake transitions. They hoped to solve this by analysing the sleep architecture in greater depth using deep learning approaches, and they hypothesised that standard sleep staging understates the sleep fragmentation of OSA patients. To verify this theory, they used deep learning-based sleep staging to identify sleep phases using overlapping 30-second epochs with 15-, 5-, 1-, or 0.5-second epoch-to-epoch length. A dataset of 446 individuals referred for polysomnography due to OSA suspicion was utilised to compare sleep architecture variations between OSA severity groups. In severe OSA with shorter epoch-to-epoch duration, wakefulness increased while REM and N3 decreased. The quantity of waking and N1 reduced while N3 rose in the other OSA severity groups. Only little changes in sleep continuity were identified across the OSA severity groups using the conventional 30-second epoch-to-epoch length. The hazard ratio demonstrating the risk of fragmented sleep was 1.14 (p = 0.39) for mild OSA, 1.59 (p 0.01) for moderate OSA, and 4.13 (p 0.01) for severe OSA with 1-second epoch-to-epoch duration. Total sleep time and sleep efficiency rose in the non-OSA group while decreasing in the severe OSA group with shorter epoch-to-epoch times. Finally, more extensive sleep analysis highlights the extremely fragmented sleep architecture in severe OSA patients, which might be underestimated using classic sleep staging. The findings emphasise the need of doing a more extensive investigation of sleep architecture for identifying sleep disorders.[35]

Torben S. Last, et,al (2021), proposed that the Portable inhalers, which carry medications to the lungs in the form of aerosols, are the conventional therapy for illnesses such as asthma, COPD, and cystic fibrosis. Spray nozzle chips, on the other hand, have been limited to cleanroom production for aqueous drug formulations due to their tiny feature sizes. They describe a spring-actuated 3D-printed swirl nozzle that sprays an aqueous medication solution at the same aerosolization time as propellant-containing inhalers. The use of two-photon polymerization allows for a tiny nozzle feature size of 100 m and device print durations of about 4 minutes, making serial massfabrication a realistic alternative. their 35 bar spring-operated swirl nozzle prototype achieves mean volumetric particle sizes of 12.5m on dosages of 100l, aerosolized in 270 ms, as quickly as a propellant-driven inhaler.[36]

Xiaomin Liu, et,al (2013), proposed that the ability to identify both the luminal and wall areas of the bronchial tree structure from volumetric X-ray computed tomography (CT) data sets is critical in distinguishing important phenotypes within a variety of major lung diseases, including chronic obstructive pulmonary disease (COPD) and asthma. However, because to their complexity, reliable assessment of the inner and outer airway wall surfaces of a complete 3-D tree structure is challenging, particularly around the branch regions. In this research, they expand a graph search-based approach (LOGISMOS) to find numerous inter-related surfaces of branching airway trees at the same time. To gather fundamental information about the tree topology, they first perform a presegmentation of the input 3-D picture. The presegmented picture is resampled along carefully chosen routes to provide a series of voxel vectors (called voxel columns). The resampling procedure makes use of medial axes to guarantee that voxel columns of the proper lengths and orientations are employed to capture the object surfaces without interference. A geometric graph is built, with its edges connecting voxels in the resampled voxel columns and enforcing the smoothness and separation restrictions on the desired surfaces. To discriminate between inner and exterior walls, cost functions containing directional information are used. The measurement of wall thickness on a CT-scanned double-wall physical phantom (designed after an in vivo imaging human airway tree) produced remarkably accurate findings over the whole 3-D tree. In bifurcating/nonbifurcating zones, the observed mean signed error of wall thickness varied from -0.090.24 mm to 0.070.23 mm. The average unsigned errors ranged from 0.16 0.12 mm to 0.20 0.11 mm. When the airway wall surface was divided into relevant subregions, the accuracy of the airway wall thickness was the same in the majority of examined bifurcation/nonbifurcation and carina/noncarina areas (p=NS). After being confirmed on phantoms, they used their approach to human in vivo volumetric CT data to show connections between airway wall thickness as a function of luminal size and airway tree formation. For tree generations 6, 7, 8, and 9, wall thickness variations between bifurcation/nonbifurcation locations were statistically significant (p 0.05). The wall thickness in carina/noncarina sections was statistically different in generations 1, 4, 5, 6, 7, and 8.[38]

A. D. Lucey, et,al (2010), proposed that the Obstructive sleep apnea is characterised by repeated closure of the upper airway. It causes excessive daytime sleepiness and has been connected to hypertension and cardiovascular disease. Previous research approximating the underlying fluid dynamics relied on geometries collected by MRI or CT scans and time-averaged across the breathing cycle. In this paper, they create an anatomically precise geometry using data obtained in vivo by an endoscopic optical approach. This enables quantitative real-time imaging of the interior cross section while being minimally invasive. A k- shear stress transport (SST) turbulence model is used to determine the steady inhalation flow field. Flow processes that create low-pressure zones on the pharyngeal sidewalls and on the soft palate inside the pharyngeal segment of minimal area are shown by simulations. Soft-palate displacement and side-wall deformations drop pressures even further in certain places, causing forces that tend to restrict the airway. These findings point to a mechanism for lateral airway closure, which has been observed clinically. Correlations between pressure and airway deformation suggest that quantitative prediction of an individual's low-pressure zones is achievable. The current predictions deserve and can lead clinical inquiry to validate and quantify the phenomenology, while the entire methodology marks a step forward towards patient-specific modelling.[39]

Narathip Reamaroon, et,al (2019), proposed that in some clinical applications, while training a machine learning algorithm for a supervised-learning task, ambiguity in the accurate labels of some patients may impair the system's performance. Because of uncertainty in the patient's condition or insufficient reliability of the diagnostic criteria, even clinical professionals may have less confidence when assigning a medical diagnosis to some patients. As a result, certain examples utilised in algorithm training may be incorrectly labelled, resulting in poor algorithm performance. However, in certain circumstances, specialists may be able to quantify their diagnostic uncertainty. They provide a robust strategy for accounting for clinical diagnostic ambiguity while training an algorithm to detect individuals with acute respiratory distress syndrome (ARDS) using Support Vector Machines. ARDS is a severely unwell condition that is diagnosed using clinical criteria that are recognised to be flawed. They express ARDS diagnosis uncertainty as a graded weight of confidence associated with each training label. To limit overfitting, they also developed a unique time-series sampling strategy to address the problem of inter-correlation among the longitudinal clinical data from each patient used in model training. When they compare their technique that accounts for the uncertainty of training labels with a traditional SVM algorithm, preliminary findings suggest that they can obtain considerable improvement in the performance of the system to predict patients with ARDS on a hold-out sample.[40]

Nguyen thi phuoc van, et,al (2019), proposed that the CW radar sensor system measures the breathing rate and compares it to the reference measurement made by the five-point touching Shimmer sensor. The breathing rate values are consistent. In the suggested system, two major time-frequency (TF) extraction feature approaches, short-time Fourier transform (STFT) and continuous wavelet transform (CWT), were applied. Some classification systems were used in these extraction processes and shown good accuracy in categorising the respiratory kinds. The study demonstrates the feasibility of developing an artificial intelligence (AI) module for a non-contact radar sensor system to alert the user about their breathing state. This study provides a smarter and more user-friendly remote vital signs sensor system. This model might be improved to incorporate more specific categories to help doctors diagnose respiratory disorders in patients. In this article, a continuous wave radar sensor system based on a vector network analyzer (VNA) is used to detect the breathing rate remotely. The measured signal from this radar sensor system is then processed for further usage. Several extracted feature algorithms are employed to obtain the breathing rate from the non-contact radar sensor system. A machine learning-based technology is being researched to identify the respiratory condition. The CW radar sensor assessed 31 subjects who were instructed to breathe in low, normal, or high levels. The measured data was also used to build a machine learning model. The CW radar sensor system monitors the breathing rate and compares it to the five-point touching Shimmer sensor's reference value. The numbers for the breathing rate are consistent. Two prominent time-frequency (TF) extraction feature techniques, short-time Fourier transform (STFT) and continuous wavelet transform (CWT), were used in the proposed system. Some classification techniques were applied in these extraction procedures, and they performed well in classifying the respiratory types. The study illustrates the viability of creating an artificial intelligence (AI) module for a non-contact radar sensor system that alerts the user about their breathing condition. This research aims to develop a better and more user-friendly remote vital signs sensor system.[37]

Sami Nikkonen, et,al (2021), proposed that Obstructive sleep apnea is diagnosed based on daytime symptoms and the frequency of breathing events throughout the night. The respiratory events are manually graded using polysomnographic recordings, which is both time-consuming and costly. As a result, automatic scoring approaches might significantly increase the efficiency of sleep apnea diagnosis while freeing up resources now required for manual scoring for use in other areas of sleep medicine. In this study, they used input data from peripheral blood oxygen saturation, thermistor airflow, nasal pressure-airflow, and thorax respiratory effort to train a long short-term memory neural network for autonomous grading of respiratory events. The data was derived from 887 in-lab polysomnography recordings. The neural network was trained on 787 patients with suspected sleep apnea, and 100 patients served as an independent test set. Manual and automated neural network scoring had a good epoch-wise agreement (88.9%, =0.728). Furthermore, with a mean absolute error of 3.0 events/hour and an intraclass correlation value of 0.985, the apnea-hypopnea index (AHI) computed from automated scoring was close to the humanly determined AHI. The neural network technique to automatic scoring of respiratory events was shown to be very accurate and in good agreement with manual scoring. The described neural network might be used to analyse massive research datasets that are impossible to score manually, and it has therapeutic promise in the future. Furthermore, because the neural network assesses individual respiratory events, the automated scoring may be readily manually evaluated if required.[42]

T. Noah Hutson, et,al (2020), proposed that the major cause of epilepsy-related mortality is sudden unexpected death in epilepsy (SUDEP), and its pathophysiological underpinnings are unclear. They set out to record and analyse simultaneous electroencephalographic (EEG), electrocardiographic (ECG), and unrestrained whole-body plethysmographic (Pleth) signals from control (WT - wild type) and SUDEP-prone mice (KO - knockout Kcna1 animal model) signals for the first time. Using multivariate autoregressive models (MVAR), they assessed all tri-organ effective directional interactions in the frequency domain across time (hours) using the generalised partial directed coherence (GPDC). SUDEP-prone (KO) animals had (p 0.001) reduced afferent and efferent interactions between the heart and the brain across the entire frequency spectrum (0-200Hz), enhanced efferent interactions from the brain to the lungs and from the heart to the lungs at high (>90 Hz) frequencies (especially during seizure activity), and decreased feedback from the lungs to the brain at low (40 Hz). These findings suggest that impairments in the afferent and efferent pathways of the holistic neuro-cardio-respiratory network may result in SUDEP, and that effective connectivity metrics and their dynamics may serve as potential biomarkers of SUDEP and seizures, respectively.[41]

Suren I. Rathnayake, et,al (2010), proposed that Algorithms based on single channel airflow data have been proven in studies to be helpful in screening for sleep disordered breathing illnesses (SDB). The diagnostic efficiency of a classifier trained on a collection of characteristics collected from single-channel airflow data is investigated in this work. The characteristics under consideration are based on recurrence quantification analysis (RQA) of measurement time series and can be supplemented by single measurements of neck circumference and body mass index. The nasal pressure (NP) is used to monitor airflow. Each of the 77 individuals undergoing PSG testing had an overnight recording utilized in the study. A classifier that predicts whether or not a measurement segment contains an SDB event was created using mixture discriminant analysis. Patients were diagnosed with SDB illness if the recording includes measurement segments that were expected to have an SDB event at a rate greater than a certain threshold. A patient is diagnosed with SDB illness if the rate of SDB events per hour of sleep, measured as the respiratory disturbance index (RDI), is greater than 15 or less than 5. They trained and assessed the classifier under each assumption, getting areas under receiver operating curves of 0.96 and 0.93, respectively, using fivefold cross-validation. To prevent unbiased estimates, they employed a two-layer framework to determine the ideal operating point and evaluate the final classifier. The estimated diagnostic sensitivity/specificity for illness categorization when RDI 15 was 71.5%/89.5% and 63.3%/100% when RDI 5 was used. These findings were obtained on the assumption that the costs of misclassifying healthy and ill people are identical, but they present a framework for varying these costs. The results show that an automated SDB screening device might utilise a classifier based on RQA characteristics acquired from NP measurements.[43]

Riku Huttunen, et,al (2023), proposed that the apnea-hypopnea index (AHI), which is the average number of respiratory events per hour of sleep, is used to diagnose obstructive sleep apnea (OSA). Machine learning algorithms for automatic AHI evaluation have recently been created, although many of them do not take into account specific sleep phases or events. The goal of this work was to create a deep learning model that could score both sleep phases and respiratory events at the same time. The premise was that scoring and subsequent AHI computation could be done only with pulseoximetry data. The deep learning models were trained using polysomnography records from 877 people with probable OSA. The same architecture was trained with three distinct input signal combinations (model 1: photoplethysmogram (PPG) and oxygen saturation (SpO2); PPG, SpO2, and nasal pressure in model 2; PPG, SpO2, nasal pressure, electroencephalogram (EEG), oronasal thermocouple, and respiratory belts in model 3). Model 1 outperformed models 2 and 3 in terms of AHI estimation (model 1 intraclass correlation coefficient (ICC) 0.946; model 2 ICC = 0.931; model 3 ICC = 0.945) and REM-AHI estimation (model 1 ICC = 0.912; model 2 ICC = 0.921; model 3 ICC = 0.883). The automated sleep staging accuracies (wake/N1/N2/N3/REM) with models 1, 2, and 3 were 69%, 70%, and 79%, respectively. AHI may be calculated automatically using pulseoximetry. Explicit grading of sleep phases and respiratory events gives visual confirmation of the automated analysis as well as information on OSA phenotypes. With a simple pulseoximetry system, automatic scoring of sleep phases and respiratory events might allow for cost-effective, large-scale screening of OSA.[44]

Lauren Samy, et,al (2014), proposed that Sleep occupies a significant amount of our lives and is essential to our health and well-being. Monitoring sleep quality can help in the medical diagnosis of a wide range of sleep and mental problems, as well as function as an indicator of various chronic diseases. Sleep stage analysis is an established biometric in identifying cardiovascular disease, diabetes, and obesity and plays a critical role in evaluating sleep quality. They provide an unobtrusive framework for identifying sleep stages based on a high-resolution pressure-sensitive e-textile bed sheet. They extract a collection of sleep-related biophysical and geometric data from the bed sheet and identify the Wake - Non Rapid Eye Movement - Rapid Eye Movement stage using a two-phase classification technique. To validate the proposed bed sheet system and its capacity to extract sleep stage information, seven all-night polysomnography recordings from healthy people were employed. In comparison to the gold standard, the disclosed system averaged 70.3% accuracy and 71.1% recall. These findings imply that in the near future, unobtrusive sleep macrostructure analysis might be a feasible choice in clinical and residential settings. When compared to existing approaches for identifying sleep stages, the presented system is inconspicuous, fits smoothly into the user's normal sleep environment, and has the added benefits of comfort, cheap cost, and simplicity.[45]

Shijie Guo, et,al (2019), proposed that the Inductance of the Respiratory System Plethysmography (RIP) is a technique for detecting the respiratory movements of the chest and belly while sleeping. Due to its severe limitations, this approach is not suited for daily usage. Many unrestricted approaches have been created, but they all share a fundamental challenge in discriminating between chest and abdominal movements, which is essential to determine the kind of sleep apnea. They suggested an unrestricted approach for distinguishing chest and abdominal motions in this work by detecting pressure changes from the chest and abdomen pressing on a mattress. The possibility of detecting respiratory movements was then studied using a flexible tactile sensor array that was put on a bed like a bed sheet. The findings of ten healthy participants (five males and five females) were compared to those obtained using RIP band sensors. It was proven that the sensor array could accurately monitor the movements of the chest and belly and calculate the breathing rate. However, depending on the subject's gender and laying position, the phase of the pressure fluctuations observed with the sensor array may differ from the outputs of the RIP band sensors. The cause was investigated using a dynamic model, which revealed that the discrepancy might have been caused by the connection of the chest and abdomen. Furthermore, the effect of mattress stiffness on pressure variations was examined. Mattress stiffness had minimal influence on the measurement, according to the data.[46]

Joanne H. Shorter, et,al (2010), proposed that Breath analysis is an effective noninvasive tool for diagnosing and monitoring respiratory disorders such as asthma and chronic obstructive pulmonary disease (COPD). Nitric oxide (NO) and carbon monoxide (CO) are airway inflammatory indicators that might reflect the severity of respiratory illnesses. They created a small, fast-responding laser device for analysing various gases by infrared absorption. The apparatus measures NO, CO, and CO2 concurrently using room temperature quantum cascade lasers.[47]

Shunya Takano, et,al (2022), proposed that Breath analysis is an effective noninvasive tool for diagnosing and monitoring respiratory disorders such as asthma and chronic obstructive pulmonary disease (COPD). Nitric oxide (NO) and carbon monoxide (CO) are airway inflammatory indicators that might reflect the severity of respiratory illnesses. They created a small, fast-responding laser device for analysing various gases by infrared absorption. The apparatus measures NO, CO, and CO2 concurrently using room temperature quantum cascade lasers. This paper presents an inhalation monitoring system that makes use of an inertial measurement unit (IMU). The IMU measures a patient's breathing motion. Incorrect inhalation consumption can be identified by comparing measurement data against data indicating correct usage. The experimental findings demonstrate the usefulness of the suggested gadget.[48]

Md. Nazmul islam shuzan, et,al (2021), proposed that Asthma, chronic obstructive pulmonary disease (COPD), pneumonia, and lung cancer are among potentially fatal respiratory diseases. The respiratory rate (RR) is an important measure of a patient's health. Continuous RR monitoring can offer early warning and hence save lives. However, because to the size and expense of the equipment, a real-time continuous RR monitoring facility is only accessible in the intensive care unit (ICU). Recent studies have recommended Photoplethysmogram (PPG) and/or Electrocardiogram (ECG) data for RR estimation; nevertheless, ECG utilisation is restricted due to its lack of availability in wearable devices. It is currently being investigated for continuous monitoring of RR due to the introduction of wearable smartwatches with built-in PPG sensors. This research offers a unique method for RR estimation that employs motion artefact correction and machine learning (ML) models using PPG signal characteristics. To decrease computational complexity and the possibility of overfitting, feature selection methods were applied. Using hyperparameter optimisation, the best ML model and feature selection method combination was fine-tuned to optimise its performance. The Gaussian Process Regression (GPR) feature selection algorithm with Fit a Gaussian Process Regression Model (Fitrgp) outperformed all other combinations, with RMSE, MAE, and two-standard deviation (2SD) of 2.63, 1.97, and 5.25 breaths per minute, respectively. If RR can be recovered effectively and reliably from the PPG signal, patients may track it at a cheaper cost and with less hassle.[49]

Ailton Siqueira Junior, et,al (2018), proposed that Respiratory patterns are often monitored and diagnosed in order to monitor and diagnose cardiovascular, metabolic, and sleep issues. Electronic equipment, such as masks used to record respiratory waveforms, frequently need the assistance of medical personnel and restrict the patient's breathing, creating pain. New strategies are being developed to address such constraints. Accelerometers are being used in a new way to estimate the respiratory waveform based on chest motion. Most known approaches, however, use a single accelerometer placed on an arbitrary thoracic site. The current study looks on the use and best placement of several accelerometers on the thorax and belly. Thirty healthy participants in three distinct postures comprise the research population. Data is collected from an array of ten accelerometers in predetermined places and a pneumotachograph as a reference using a custom-made microcontrolled system. The optimum sensor positions are determined by doing an optimal linear reconstruction of the reference waveform using accelerometer data with a minimum mean square error. The research reveals that right-side locations contribute more frequently to ideal respiratory waveform estimations, which a reasonable conclusion is given that the right lung has a bigger capacity than the left lung. Furthermore, they demonstrate that the respiratory waveform can be recovered blindly from accelerometer data using independent component analysis. Finally, in clinical contexts where the use of masks may be prohibited, linear processing of several accelerometers in ideal placements can successfully retrieve breathing information.[50]

Suk Jin Lee, et,al (2012), proposed that Complicated breathing behaviours, such as uncertain and irregular patterns, might impair the predictability of respiratory motion for precision radiation dosage administration. So far, research on irregular breathing patterns has been limited to just severe inspiration and expiration respiratory monitoring. Using breathing traces obtained at a Cyberknife treatment facility, they retrospectively classified breathing data into numerous groups based on extracted feature metrics collected from many patients' breathing data. The innovative aspect of this article is that the neural network-based classifier can give therapeutic worth for the statistical quantitative modelling of irregular breathing motion based on a regular ratio expressing how many regular/irregular patterns occur within an observation interval. They offer a novel method for detecting abnormal breathing patterns using neural networks, in which the reconstruction error is utilised to generate a distribution model for each breathing class. To determine whether or not the present breathing patterns were regular, the suggested irregular breathing categorization employed a regular ratio. The suggested irregular breathing pattern detector's sensitivity, specificity, and receiver operating characteristic curve were investigated. The suggested irregular breathing classifier was validated by the experimental findings of 448 patients' breathing patterns.[51]

Surajit Bagchi et,al (2019), proposed that there is a global need to develop noninvasive, simple, quick, selective, low-cost, and portable illness assessment technologies. When compared to standard analytical procedures, enzyme-based bio-sensing systems offer all of these potential benefits. This paper proposes a carbonic anhydrase enzyme (CA) (E.C. 4.2.1.1)-based cost-effective, highly selective, and reproducible CO_2 biosensing system that can accurately measure CO_2 concentration (ppm level) in expired breath to provide valuable information for assessing the subjects' respiratory disorders. CA is extracted from spinach leaves before being immobilized on an electrode assembly. When the assembly comes into contact with aqueous CO_2, it produces a detectable electrical signal (mV). The sensor has a linear response from 160 ppm to 2677 ppm of CO2 concentration dissolved in water, good sensitivity (0.132mV/ppm), and a rapid reaction time of 12 seconds. Repeatability, shelf life (5 months), re-usability (20 times), and selective reactivity to CO2 molecules in exhaled breath are among the attributes. The biosensor's viability in a proper set-up for home-based monitoring of CO2 in exhaled breath has been presented and justified. The technology demonstrated a strong correlation between sensor findings and recognised clinical tests.[52]

Styliani A. Taplidou, et,al (2010), proposed that Wheezes are melodic breath noises that often indicate the presence of a lung obstruction, such as asthma or chronic obstructive pulmonary disease (COPD). Although numerous research have been conducted to address the problem of wheeze detection, only a few scientific works have concentrated on the examination of wheeze features, specifically their time-varying nonlinear characteristics. The goal of this research is to uncover and statistically analyze the nonlinear properties of wheezes and their evolution over time as represented in the quadratic phase coupling of their harmonics. To that end, the continuous wavelet transform (CWT) is used in conjunction with third-order spectra to define the analysis domain, in which the nonlinear interactions of wheeze harmonics and their time variations are revealed by incorporating instantaneous wavelet bispectrum and bicoherence, which provide instantaneous biamplitude and biphase curves. Based on this nonlinear information pool, a set of 23 characteristics for nonlinear analysis of wheezes is provided. Two contrasting viewpoints, general and detailed, relating to average performance and locales, respectively, were employed in the feature set building to encapsulate trends and local behaviors evident in the nonlinear interplay of the harmonic constituents of wheezes over time. The suggested feature set was tested using a dataset of wheezes obtained from a lung sound database from adult patients with documented asthma and COPD. For all data sub-groupings, the statistical examination of the feature set indicated discriminating abilities between the two diseases. When the total breathing cycle was examined, all but one of the 23 features showed a statistically significant difference between the COPD and asthma pathologies, whereas for the sub-groupings of inspiratory and expiratory phases, 18 out of 23 and 22 out of 23 features, respectively, exhibited discrimination power. This paves the door for wavelet higher order spectral characteristics to be used as an input vector to an effective classifier. This, it appears, would combine the inherent properties of wheezes inside computerized diagnostic instruments for more efficient examination.[56]

Neil M. White, et,al (2017), proposed that More than 300 million individuals worldwide are affected by respiratory disorders such as asthma and chronic obstructive pulmonary disease (COPD). Devices such as the pneumotachograph are currently utilized in clinical settings to measure inhalation, expiration, and respiration cycle, but they are physically bulky and unsuitable for patient usage at home. A tiny, lightweight respiration sensor for use in the home allows patients to easily monitor their breathing rate. NASA originally designed the capaciflector as a capacitive proximity sensor for robot collision detection. They discovered that by connecting the gadget to the chest, they can detect breathing patterns in individuals. They cover the modelling, fabrication, and testing of a capaciflector for use as a respiration sensor, as well as how it may be interfaced to a microcontroller to allow wireless data transfer over a Wi-Fi signal.[57]

Wenyang Xie, et,al (2019), proposed that it is challenging to obtain true and useful feedback on regimen adherence from patients while treating asthma and chronic obstructive pulmonary disease (COPD). Current intelligent pharmaceutical best practices do not support face-to-face or oral reporting modalities. This study describes a method for tracking and analyzing inhaler consumption on a daily basis. A portable electronic gadget attached to the inhaler detects motion with an accelerometer and capacitive sensors and captures noises with an inbuilt digital microphone when the inhaler is in use. In terms of analysis, a hidden Markov model with a Gaussian mixture model is used to extract sound characteristics and identify breath phases. In addition, a feature template is created and utilized to search for and detect "canister pressed" occurrences. The method gives objective feedback by assessing asthma and COPD patients' drug adherence. Although there is rising interest in asthma medication adherence, there is still a relative lack of research and compliance devices in this area; the monitoring system can assist clinicians better assess the patient's condition and determine an appropriate treatment strategy. At the same time, system feedback can help patients improve their self-management.[58]

Xingzhe zhang, et,al (2021), proposed that a multi-channel stethograph system with 16 acoustic sensors was created and developed as an electronic auscultation system for graphic recording of heart, lung, and trachea (HLT) sounds. The multi-channel stethograph system was built by encasing 16 microphone-based acoustic sensors in CNC machined Delrin R housing casings with diaphragms. 14 of the 16 acoustic sensors were inserted in a memory foam pad, and two were placed directly on the heart and trachea to collect noises from the lungs, heart, and trachea at the same time. For signal conditioning, the noises collected by the 16 acoustic sensors were routed via a specifically designed and manufactured 16-channel PCB. To collect and wirelessly transfer data from the 16-channel PCB to a Wi-Fi enabled device such as a PC/tablet, a National Instruments (NI) 9205 data acquisition device (DAQ) and an NI 9191 wireless chassis were utilized. To capture data from the DAQ, a custom LabVIEW programme was created on a Wi-Fi capable PC/tablet. Furthermore, a MATLAB programme was created to convert the collected data from the acoustic sensors into 16 audio files (for audio playback) and display the waveforms in time and frequency domains, as well as a spectrogram, allowing visual study of any anomalous patterns in intake and exhalation. This gives crucial information on the existence of crackles, rhonchi, and wheezing noises, as well as aberrant heartbeat and breathing rate, which aids in analyzing the heart and lungs' state. By giving objective evidence, the graphically presented HLT sounds will aid clinicians in the clinical diagnosis and monitoring of lung and heart problems, including chronic obstructive pulmonary disease (COPD), asthma, pneumonia, and congestive heart failure.[59]

Juan Yang, et,al (2020), proposed that they investigated the nature of sleep-related linkages between the CNS and the cardiorespiratory system. Overnight polysomnography recordings were made on 33 healthy adults. The relative spectral intensities of five frequency bands, three ECG morphological characteristics, and breathing rate were calculated using six EEG channels, three ECG morphological features, and respiratory rate. The synchronous feature series were interpolated to 1 Hz to preserve the high temporal resolution required to recognize quick physiological variations. CNS-cardiorespiratory interaction networks were built for each EEG channel, and directionality was assessed using multivariate transfer entropy. Finally, the interaction of Deep, Light, and Rapid Eye Movement (DS, LS, and REM) sleep was studied. Bidirectional connections occurred in central-cardiorespiratory networks at all phases of sleep, with the predominant pathway being from the cardiorespiratory system to the brain. The degree of information transmission from heart rate and respiration rate to brain increased progressively with the sequence of REM, LS, and DS. Furthermore, the occipital lobe appeared to receive the most cardiorespiratory system input during LS. Finally, it was revealed that multiple ECG morphological characteristics were involved in various central-cardiac and cardiac-respiratory interactions. These findings provide new light on sleep regulating systems by disclosing details about CNS-cardiorespiratory interactions during sleep. Their strategy might help researchers better understand the pathological cardiorespiratory consequences of sleep disturbances.[60]

Minsoo Yeo, et,al (2021), proposed that the purpose of this study is to describe an automated approach for detecting respiratory events in patients utilizing electrocardiogram (ECG) and respiratory signals. The suggested approach was created utilizing polysomnogram (PSG) and patch-type device data. For algorithm development and assessment, data from 1,285 patients were used in total. The suggested approach included detecting respiratory events and calculating the apnea-hypopnea index (AHI). Machine learning methods such as linear discriminant analysis, quadratic discriminant analysis, random forest, multi-layer perceptron, and the support vector machine (SVM) were used to apply handcrafted characteristics from ECG and respiration data. When utilizing SVM, high performance was established, with an overall accuracy of 83% and a Cohen's kappa of 0.53 for minute-by-minute respiratory event identification. The correlation coefficient between the PSG-derived reference AHI and the proposed method's calculated AHI was 0.87. Furthermore, patient categorization based on an AHI threshold of 15 demonstrated 87% accuracy and a Cohen's kappa of 0.72. The suggested approach improves performance by concurrently recording the ECG and breathing signals. Overall, because open datasets are used, it may be leveraged to reduce the development cost of commercial products.[61]

Pouya soltani zarrin, et,al (2020), proposed that Chronic obstructive pulmonary disease (COPD) is a potentially fatal lung condition that is a major source of morbidity and mortality across the world. Although a cure has yet to be discovered, continuous monitoring of biomarkers that show disease progression is critical for good COPD management. In a Point-of-Care (PoC) setting, precise assessment of respiratory tract fluids such as saliva is a potential technique for staging illness and predicting impending exacerbations. However, reliable results need concurrent evaluation of patients' demographic and medical factors. As a result, in a PoC context, Machine Learning (ML) techniques can play an essential role in analyzing patient data and giving complete findings for the detection of COPD. As a result, the goal of this research was to apply ML methods to data obtained from characterizing saliva samples of COPD patients and healthy controls, as well as their demographic information, for PoC illness detection. A permittivity biosensor was utilized to characterize the dielectric characteristics of saliva samples for this purpose, and ML methods were then applied to the collected data for classification. The XGBoost gradient boosting technique achieved 91.25% classification accuracy and 100% sensitivity, making it a suitable model for COPD assessment. In the future, integration of this model on a neuromorphic device will allow for real-time evaluation of COPD in PoC at a cheap cost, low energy consumption, and excellent patient privacy. Furthermore, continuous monitoring of COPD in a near-patient setting will allow for improved management of disease exacerbations.[53]

Heng Zhao, et,al (2018), proposed that a noncontact breathing problem identification method for recognizing abnormal breathing patterns is suggested in this research. A Doppler radar-based sensor module and a machine-learning-based respiratory problem identification module are included in the suggested system. To precisely record the time-domain breathing waveform, a custom-designed 2.4-GHz continuous wave (CW) digital-IF Doppler radar is used as the radar sensor module. Then, using selected features and optimized classifiers, a recognition module is created. Four sets of tests were conducted in order to thoroughly examine the proposed system. Using the linear SVM classifier with seven specified features, the suggested system achieves 94.7% classification accuracy in laboratory testing. Clinical trial results show the possibility of long-term breathing condition detection with excellent accuracy and robustness, as well as the potential of the suggested approach for auxiliary illness diagnosis.[54]

Zhe Cao, et,al (2012), proposed that the use of microsensors in a wireless portable monitoring system for respiratory disorders is proposed. The monitoring system is made up of two sensor nodes that communicate with Bluetooth transmitters to assess the user's respiratory airflow, blood oxygen saturation, and body posture. The monitor's usage of a micro-hot-film flow sensor allows it to capture comprehensive respiratory characteristics that may be used to diagnose obstructive sleep apnea, chronic obstructive pulmonary disease, and asthma. The system may function as a sleep recorder as well as a spirometer. Furthermore, telemedicine is made possible by a mobile phone or a PC connected to the Internet that serves as a monitoring and transmission terminal. Several studies were carried out to test the feasibility and efficacy of the proposed system for monitoring and diagnosing OSA, COPD, and asthma.[55]

Stavros Nousias et,al (2018), proposed that This study introduces an integrated mHealth system that gives patients with real-time personalized feedback to check correct medicine administration, educate them, and assist them in avoiding frequent errors. The detection of correct inhaler use is based on traditional and data-driven feature extraction and classification approaches used to identify four events (inhaler activation, inhalation, exhalation, and background noise). The suggested technique achieves 98% classification accuracy, greatly surpassing current and related state-of-the-art approaches. Finally, straightforward feedback interfaces were developed in the form of a virtual guiding agent coupled with the mobile application, allowing patients to follow their action plan and analyze their inhaler technique in a more engaging way. Extensive simulation experiments involving twelve people confirmed the efficacy of the proposed methodologies in both indoor and outdoor settings.[62]

Gaetano Scebba et,al (2020), proposed that Many therapeutic applications require continuous monitoring of respiratory activity in order to detect respiratory events. Near- and far-infrared spectrum cameras can be used to monitor respiration without requiring touch. However, present technologies are not strong enough to be employed in clinical settings. For example, they do not accurately assess the respiratory rate (RR) during apnea. They offer a unique technique based on multispectral data fusion for calculating RR even during apnea. The method handles the RR estimate and apnea detection duties separately. Respiratory data is taken from several sources and put into an RR estimator and an apnea detector, whose results are combined to provide a final respiratory activity estimate. they examined the system retrospectively using data from 30 healthy persons who conducted a variety of regulated breathing activities while laying supine in a dark environment, replicating central and obstructive apneic occurrences. Combining different respiratory data from multispectral cameras increased the root mean square error (RMSE) accuracy of RR estimate from up to 4.64 monospectral data to 1.60 breaths/min. The median F1 scores for identifying central and obstructive apnea (0.75 to 0.93) also improved. Furthermore, independent apnea detection resulted in a more robust system (RMSE of 4.44 vs. 7.96 breaths/min). their discoveries may pave the way for the use of cameras to monitor vital signs in medical applications.[64]

SECTION III

Conclusion

Machine learning (ML) has developed as an effective method for analyzing vast volumes of data and detecting patterns that may be used to forecast and categories respiratory illnesses. ML algorithms have been effectively used to a number of respiratory medical applications, including asthma risk prediction, respiratory sound categorization, and automated detection of respiratory events.

This paper covered current breakthroughs in ML-based approaches for respiratory illness diagnosis, monitoring and using Assist device for curing, as well as their works, which include:

- Data quality: The data used to train ML models is important to their success. Poor-quality data might result in biased models that are not applicable to real-world scenarios.
- Model interpretability: ML models can be difficult to interpret, making it difficult to comprehend why certain predictions are made. This can make it challenging to trust ML model results and apply them in clinical decision-making.
- Clinical validation: To guarantee that ML models are accurate and useful in real-world contexts, they must be verified in clinical trials.

Methods based on machine learning have the potential to transform the diagnosis, monitoring and using Assist device for curing of respiratory disorders. As ML models improve in accuracy and interpretability, they are expected to become more widely used in clinical practice.

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