COPD Patient Monitoring by Virtue of Internet of Things: A Review

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Abstract

The disease that often affects the lung by blocking the airways is known as Chronic Obstructive Pulmonary Disease (COPD). There are several cause of COPD disease and especially smoking behaviour is the major cause of chronic illness. However, offering treatment for COPD patients is a challengeable task, because the symptoms and actions are not similar for all patients. To diminish this problem, the technology called Internet of Things (IoT) is been introduced to monitor the patients and submit the report with a wide range of exactness rates. Furthermore, IoT is designed with different sensor hubs to sense the patient's body condition with high accuracy. Thus, identification of the disease severity rate is possible by monitoring several biological parameters using different processes and sensors. Analysis of parameters are performed using an efficient Machine Learning (ML) or Deep Learning (DL) approach in a suitable platform. By, using IoT technology, anybody from anywhere can able to access the medical specialist suggestion based on their body conditions. The current review article has aimed to present the uses of IoT in COPD patient monitoring in different ways as well as the function of different models are compared in the form of graphs.

Keywords: *Biological Parameters, Chronic Diseases, Internet of Things, Sensors, Severity Prediction.*

1. Introduction

Chronic Obstructive Pulmonary Disease (COPD) [1], the world's third most dangerous disease, has dramatically increased the death rate [2]. It is a form of lung disease in which the airflow from the lungs has been stopped [3]. As a result, cough, wheezing, breathing difficulty, and mucus are all indications of COPD [4]. The main cause of COPD is long-term cigarette smoking [5]. Furthermore, asthmatics may be more susceptible to COPD since asthma combined with smoking increases the risk of COPD [6]. Furthermore, COPD patients are susceptible to respiratory infections such as the flu, cold, and pneumonia [7]. To monitor the COPD patient regularly, a novel pressure handling spirometer was equipped [8]. Moreover, its operating platform was based on the cloud android framework. As a result, the mobile-based framework was successfully used to track COPD patients' movements [9]. Various types of smart applications are employed in mobile devices for patient-physician communication [10], which are also equipped in both software and real-time platform. The finest relationship among healthcare professionals and patients has been provided maximum support to manage COPD [11], which was depending upon smooth communication. For that, mobile apps are very useful to bridge the relationship [12].

The allotment of medical sources is segregated according on COPD severity in the latest hierarchical-based medical architecture [13]. It is straightforward to obtain medical advice from certain doctors using smart technological devices [14]. Also, the doctors' recommendations are written in broad strokes [15], which makes it easier for patients to follow the doctor's advice without misunderstanding [16]. The disadvantage of this medical service is that some doctors only have limited time to provide the recommendation [17]. Cough is frequently associated with pulmonary illness, making it a sign of a variety of lung diseases [18]. A cough sensor is attached to each body to monitor the patients who all have COPD [19, 20]. The different lung-based disorders are segregated using feature extraction algorithms [21]. Furthermore, the discipline of big data offers a variety of medical fields that can provide healthcare for a variety of people with various conditions [22]. The information system's analytics have gathered a large amount of IoT data in order to make the best selection for biological parameter monitoring [23]. Figure 1 shows the factors that cause COPD.

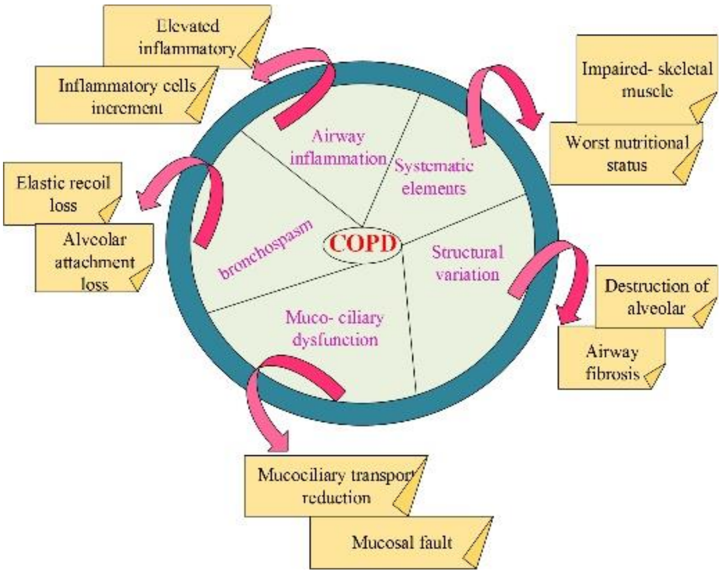
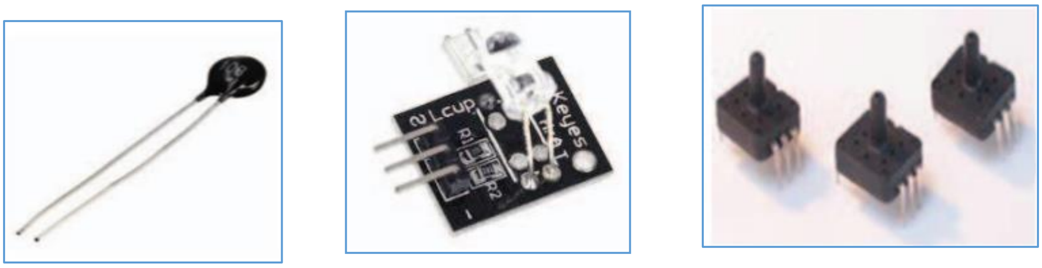


Figure 1. Factors of COPD Disease.

2. Respiratory Monitoring with IoT

Different COPD disease treatment techniques are examined in order to discover the best one [24]. The analysis confirmed that a multi-model approach is better for managing COPD [25]. Furthermore, this comparison evaluation aids future researchers in developing an effective model [26]. The system was trained on both normal and pathological datasets for the inquiry, with aberrant data being similar to normal data in some rare circumstances [27]. The categorization accuracy was lowered in the situation.



A B C

Figure 2. A) Body temperature sensor, B) Heart rate sensor, C) Blood pressure sensor [32].

To improve COPD disease, David Naranjo-Hernández et al [28] proposed respiratory monitoring, in which the severity of COPD disease was assessed based on COPD patients' breathing rates. As a result, a chest electrode was used to assess the breathing rate. Calculating the intended copy there are nine COPD patients in total, three women and six men. Table 1 contains detailed information about each subject.

Table 1. Patient Details before Monitoring

Body parameters	Maximum value	Average value	Minimum value	SD
Age	76	64	55	6.6
Index (body mass)	39.3	29.2	18.7	6.3
height	185	167.6	152	10.3
weight	1006	81.1	58	14.9

In other cases, the respiratory rate of COPD patients was predicted using a data mining technique and sensors [29]. Three types of sensors are fitted to COPD patients to collect body condition data: a heart rate calculating sensor, a blood pressure calculating sensor, and a temperature estimating sensor, as shown in fig.2. Furthermore, an Arduino microcontroller was utilised to read the sensed data [30, 31].

For this investigation, data from 500 individuals with three different signals related to their body state were collected. The supervised learning approach was used to assess the health of COPD patients and the severity of their disease [32].

People with chronic diseases have had to keep track of the body's vital signs on a frequent basis. Monitoring the respiratory rate is critical in this situation; it is calculated by counting the number of breaths per minute. Because respiration rate is often reliant on a particular physiological condition, it may differ from one patient to the next [33].

A V Radognaetal [34] created the mechanical ventilator to collect COPD patients' breath rates and segregate the low breath rate data. The additional disease analysis process was carried out after the low breath rate data were separated. Fig. 3 depicts the process of IoT-based monitoring.

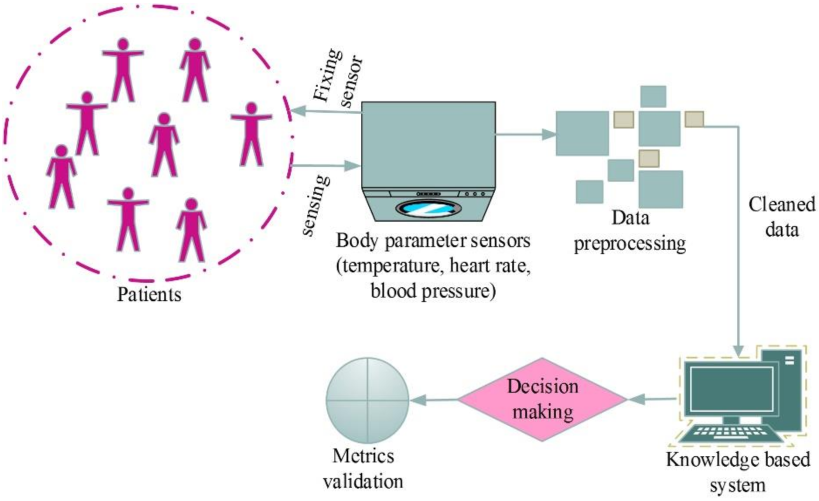


Figure 3. Patient Monitoring System using IoT.

The home-ventilo-based therapy was created to measure physiological activity. The proposed device was initially attached to the human body to monitor bodily parameters. Furthermore, an application for knowing the doctor's recommendations from their home was made in a smart device, and with the help of that generated application, the patient can remotely employ the services [35].

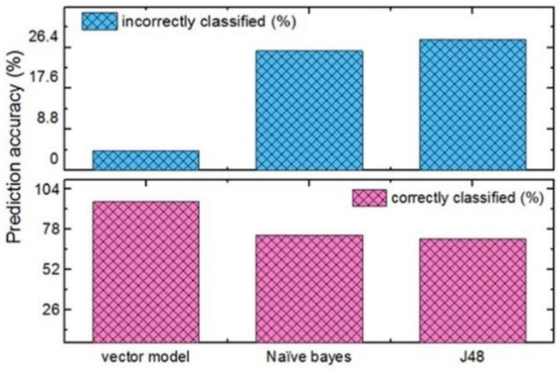


Figure 4. Respiratory Rate Classification Accuracy.

In addition, three models are used for respiratory rate prediction: vector model, naive Bayesian, and J48, all of which are enlarged in Fig. 4, and the additional metrics are graphically depicted in Fig. 5.

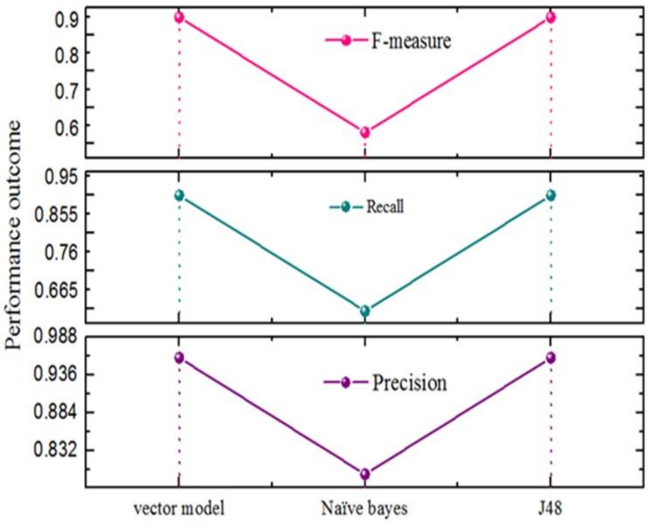


Figure 5. Performance Evaluation of F-Measure, Recall, and Precision.

3. Monitoring of Body Acceleration

In the medical business, DL and ML were successfully used to categorize disease categories and severity rates. As a result, the ML and DL neural models are used in medical applications such as electroencephalography (EEG), X-ray, and so on. Furthermore, by using ML models, several patients' data may be trained at once, and the desired analytical output can be reached with a high exactness score. As a result, the time spent on disease analysis has decreased. Furthermore, bodily motion or activity should be tracked for precise severity recognition. Fabio Pitta et al [36] have developed a body acceleration detection model for this purpose. The main disadvantages of this method are that if people walk smoothly, their walk acceleration is difficult to detect.

To reduce the death rates associated with COPAD disease, more effective and stable management strategies must be established. Furthermore, many individuals in rural regions are unaware of this terrible disease and its severity. Jing Zhang et al [37] proposed a unique system based on mobile with an IoT device to improve their lifestyle. A body sensor was implanted in persons living in rural areas, and their condition was monitored using mobile phones. Simultaneously, the appropriate ideas were delivered via mobile phones by certain doctors or medical agencies, and individuals could then follow those suggestions and stay informed about specific ailments. With less cost, smart and quick information about each unique body condition is available. Communication was interrupted under this technique if the electronic equipment performed poorly.-ThaoThiHo et al [38] created a 3D convolution neural network for better COPD severity estimate to map the disease severity. Finally, the time graphs representing the disease kind and affection rate are exhibited. It also achieved 89.3 percent illness categorization accuracy and 88.3 percent sensitivity metrics. The process was completed with high precision and in a short amount of time.

A machine learning framework was used to assess the severity of COPD rate in a short period of time for the quick analysis. In addition, the patient's lung pictures serve as a dataset for calculating COPD parameters. Finally, the suggested technique is evaluated using a statistical test. Multiple patients' data is analysed in a short period of time, and image noise tends to reduce accuracy. Cough is the most common symptom of most respiratory disorders, hence the characteristics of cough audio signal provide insight into the state of respiratory organs [39, 40]. So, with the help of IoT devices, a deep neural framework was used to extract features from the cough audio data. Furthermore, body sensors were inserted into the human body to detect the cough of COPD patients [41]. An equal number of normal and atypical coughs were gathered for the cough dataset. The anomalous cough signals are isolated from the normal cough signals during cough signal processing. It has a classification accuracy of 95% for cough signals [42]. Finally, the various types of cough sickness were successfully identified. It has, however, a high mistake rate. As a result, Fig. 6 contains a summary of the examined literature.

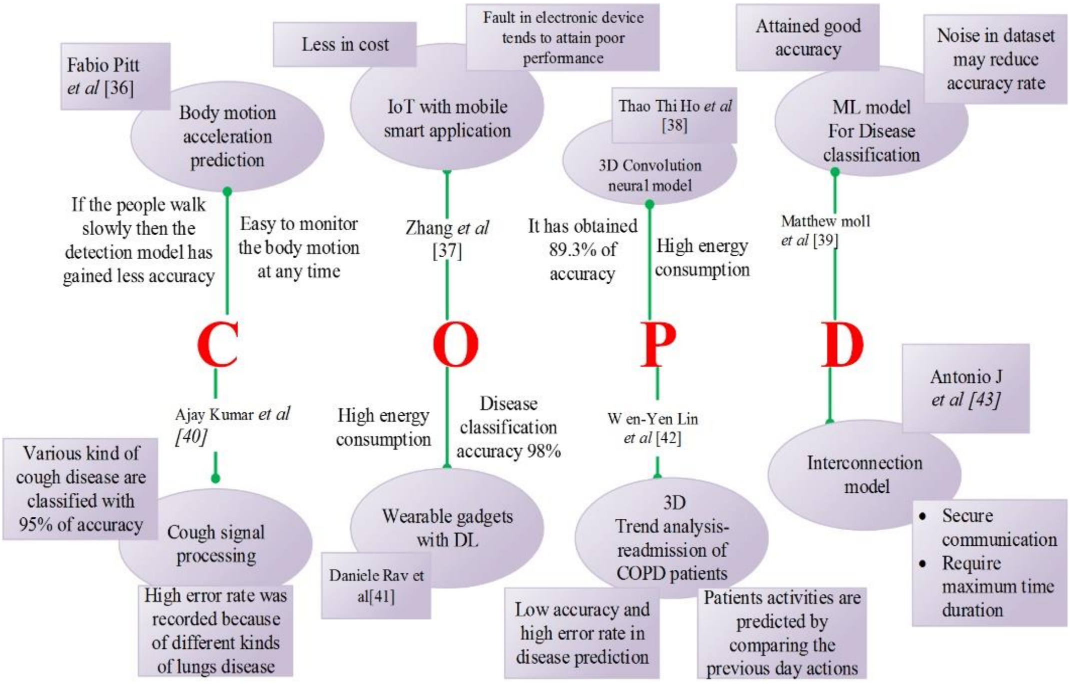


Figure 6. Summary about Few Literature Works.

The recognition of human activity has been accomplished using a time-series dataset [43, 44]. Body sensors were successfully incorporated in the digital healthcare framework to sense the body condition and biological parameters [45, 46]. Wearable devices, cellphones, and the Internet of Things have recently become popular equipment for regularly monitoring human gaits [47, 48] . Aside from that, there are several profitable sensor products [49] such as Fitbit, Apple Watch, Smartphone apps, and the Microsoft Band all include physiological data [50, 51]. Deep learning can be used to extract features from sensed data for severity identification [52] . It has a 98 percent infection classification accuracy, but electronic devices such as the Internet of Things have shown more power.

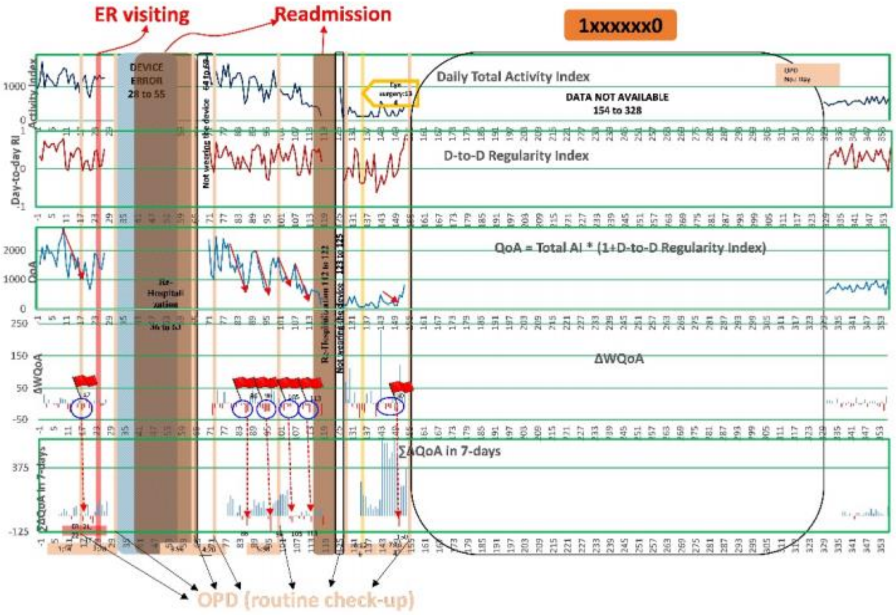


Figure 7. Readmission Trend Analysis.

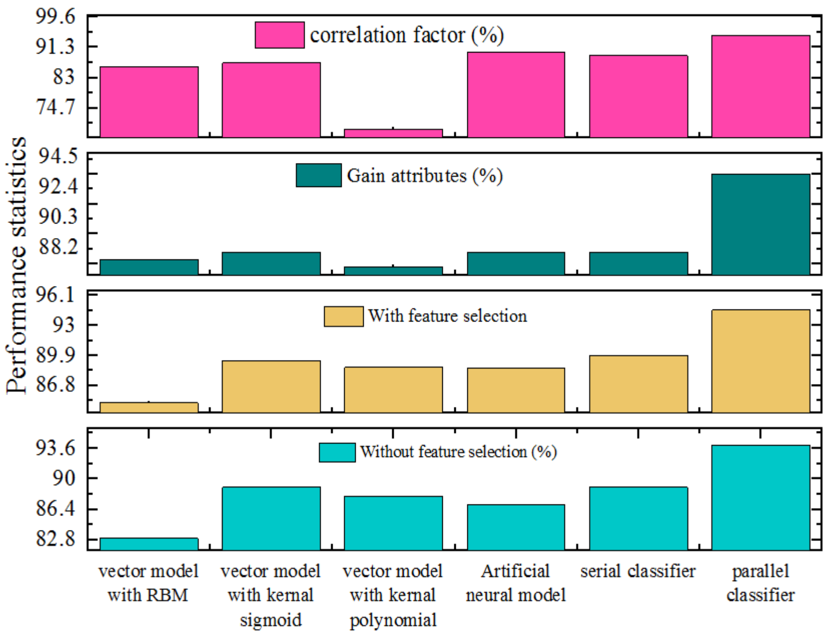


Figure 8. Outcome Assessment of Surveyed Literature.

Wen-Yen Lin *et* al colleagues [53] examined the risk of COPD patients returning to the hospital after 30 days of medication. To assess the patient's risks, a trend analysis model was created utilising mathematical formulas in a systematic manner.

$$\Delta PoB_i = (PoB_i - PoB_{i-1}) / PoB_{i-1} * 100$$

Here, PoB_i signifies the change in motion of one day, and i is used to compare the previous day's $(i-1)$ action.

EEE 1073 is an extended standard for healthcare frames that includes health profiles.

Furthermore, this approach has improved communication while avoiding signal loss [54, 55]. In the healthcare system, a narrow communication range on a wearable electronic device makes data broadcasting challenging [56, 57]. Fig. 7 shows the readmission framework in greater depth.

The ML strategy is the radial basis model, and the classification approach is the analyzed vector scheme. Furthermore, the vector classification mechanism's default kernel is radial basis. Fig. 8 depicts the performance of each plan.

4. Management Procedure for COPD Disease with IoT

Sensors are increasingly important in the healthcare business [58]. For a secure and precise forecast of illness severity rate, specialists need reliable data obtained directly from the patient's body [59]. Different body parameters can be used to monitor human health, and different sensors should be used for different body parameters [60]. As a result, these sensor-based electronic devices are referred to as wearable devices [61, 62].

Wearable devices are the most common technique to gain access to patient data without jeopardizing security; all poses are acquired via wearable sensor devices [63, 64]. As a result, data from hospitals, medical institutions, and other organizations was transferred to the cloud. To observe the patient's activities and functions of all bodily parameters, Christos C *et al* [65] used both a respiration and a body motion acceleration sensor. Finally, the data was recorded in a Broadway-style format. To de-noise the obtained data, the respiration signals required a pre-processing program with adequate feature extraction. Furthermore, the respiration rate was assessed using the respiration reference signal. Ioanna Chouvarda et al [66] proposed an integrated method to manage many diseases, which has supported various types of disease prediction. WELCOME was also given to the anticipated replica; it is a form of application that is run in a software environment and may include several gadgets.

The electrocardiographic signal is the most modern bio-signal for monitoring and analysing a patient's health status [67]. Furthermore, the wearable device with heart rate and diabetes sensor has enabled patients to track their bodily status for several days. Diego A et al [68] created an activity training program to isolate the aberrant heart rate. For this software, 29 patient data were trained, with people ranging in age from 18 to 68. The fitted heart rate sensor may initially collect each person's heart rate for 1 minute, after which the abnormal heartbeat was specified based on the normal heartbeat situation.

Table 2: Merits and Limitations in IoT Based COPD Management

Author	System	Merits	demerits
Christos C *et al* [44]	Intelligent system	It has obtained wide range of chronic infection prediction accuracy. Moreover, for the high exactness prediction acceleration and respiratory sensors were used	The sensor gadgets have needed more power
Ioanna Chouvarda et al [65],	WELCOME	It has the capacity to detect several kinds of diseases within one single monitoring	High delay time was

			recorded to broadcast data
Diego A et al [66]	Exercise program	The abnormal heartbeat rate is specified with the help of heart monitoring sensors	It takes long time period for execution
MoeenHassanalieragh et al [73]	Secure cloud model	Security frames were developed to secure the sensed data during data broadcasting. Here, heart rate sensors are used to calculate the heartbeat.	Power consumption was too high because of powerful sensor
Gutte et al [74]	Raspberry Pi – respiratory rate and body action (movement monitoring)	Less expensive in cost	It has required high resources to complete the task

The context-based data-aware paradigm was developed with sensing functions to improve security in communication channels [69, 70]. As a result, attack vulnerabilities are prevented during data transmission [71, 72]. Here, strong sensors were utilized to value each chronic patient's heartbeat; the sensors required more power to detect the event [73]. As a result, the model's constraint is a large range of power observations due to powerful sensors. The author of one paper used a Raspberry Pi sensor to track the rate of breathing. The Raspberry Pi board was directly connected to the smart system or PC in this case, and it updated the patient's breathing rate every minute. Furthermore, an acceleration-based sensor was installed on the patient's bed to determine the pace of movement. The patient's bodily movements were then recorded, and the required values were calculated. Furthermore, the disease severity range was computed using that value [74].

5. Performance Assessment

Because the IoT sensed data is kept in the cloud platform, the IoT healthcare system is frequently integrated with cloud platforms. As a result, the cloud service platform provides a wide range of capabilities for carrying out healthcare tasks.

Different types of spirometers were used to assess the biological parameters of COPD patients. Furthermore, the sensor-based monitoring system is frequently linked to a mobile phone or other smart device in order to get notifications on body functions at any time and from any location.

The misclassification of prediction is given as error rate or occurrence of error during disease detection. Figure 9 also shows the exactness score of disease severity detection. Figure 10 shows the evaluation error rate.

Furthermore, some studies have shown that using a powerful sensor consumes more energy than using a traditional sensor type. As a result, the IoT-based health monitoring paradigm has necessitated greater resources to carry out the sensing process.

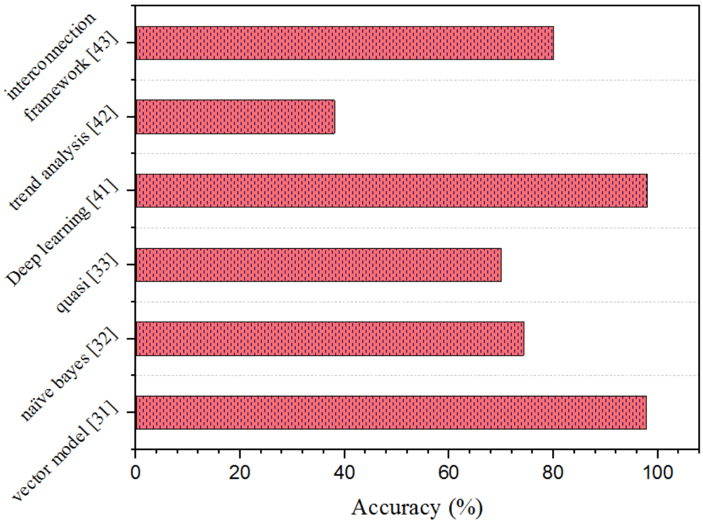


Figure 9: Accuracy Comparison of Various Techniques.

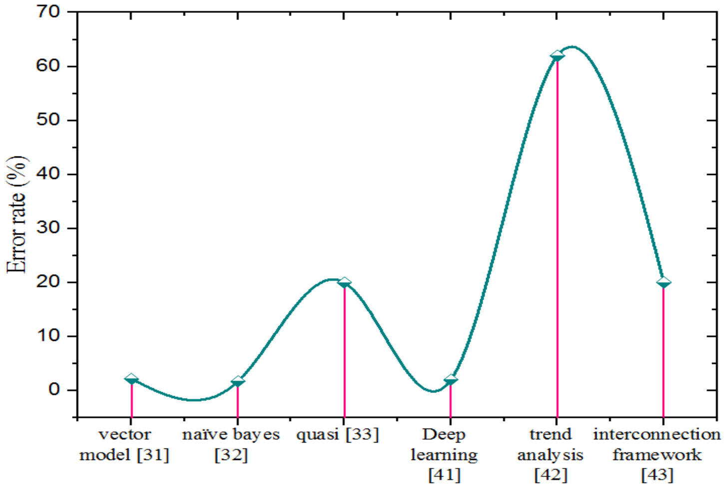


Figure 10: Assessment of Error Rate.

6. Conclusion

Several models were proposed for estimating the COPD illness rate by monitoring lung disease patients using sensor-based IoT devices. Because of factors such as large datasets, difficult data, data inaccuracy, and inefficient algorithms, many techniques can produce low exactness scores for infection prediction. Figure 11 depicts the area explored in this review study graphically.

Nowadays, the digital world embraces innovative technologies that promise to integrate a variety of electronic devices. Furthermore, IoT is a sophisticated mechanism that is simple to implement in our daily lives to improve our quality of life. As a result, the Internet of Things has become user-friendly in a variety of fields, including medical, monitoring, and so on.

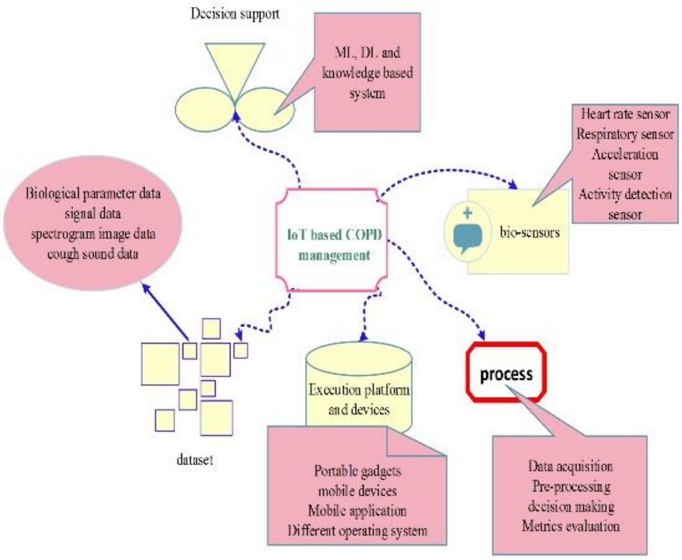


Figure 11. Overview of Present review.

The uses of IoT gadgets in COPD illness monitoring are detailed in this article, and the severity score of the disease is derived by evaluating the biological parameters of each patient. Furthermore, the current evaluation has demonstrated that data collecting is the most important duty for COPD treatment and disease severity analysis. As a result, a heuristic model with a hybrid deep neural frame will improve data sensing in the future by achieving the highest sensing accuracy.

References

[1] J. Dunbar-Jacob, 2001. M. K. Mortimer-Stephens, "Treatment adherence in chronic disease," J. Clin. Epidemiol., vol. 54, no. 12,pp. S57-S60.

[2] S. G.Deeks, S. R.Lewin, D. V.Havlir, 2013. "The end of AIDS: HIV infection as a chronic disease," The Lancet, vol. 382, no. 9903, pp. 1525-1533.

[3] D. J. P. Barker, 2001. "A new model for the origins of chronic disease," Med. Health Care Philos., vol. 4, no. 1, pp. 31-35.

[4] J. L. Phillips, D. C.Currow, 2010. "Cancer as a chronic disease," Collegian, vol. 17, no.2, pp. 47-50,

[5] D. J. P. Barker, 2012. "Developmental origins of chronic disease," Public health, vol. 126, no.3, pp. 185-189.

[6] J. K.Willcox, S. L. Ash, G. L. Catignani, 2004. "Antioxidants and prevention of chronic disease," Crit. Rev. Food Sci. Nutr., vol. 44, no.4, pp. 275-295

[7] C.Eiser, 1990. "Psychological effects of chronic disease," J. Child Psychol. Psychiatry, vol. 31, no. 1, pp. 85-98.

[8] B. G.Celler, N. H. Lovell, J.Basilakis, 2003. "Using information technology to improve the management of chronic disease," Med. J. Aust., vol. 179, no.5, pp. 242-246.

[9] D. De Ridder, R.Geenen, R.Kuijer, H. van Middendorp, 2008. "Psychological adjustment to chronic disease," The Lancet, vol. 372, no.9634, pp. 246-255.

[10] W. C.Cockerham, B. W. Hamby, G. R. Oates, 2017. "The social determinants of chronic disease," Am. J. Prev. Med., vol. 52, no.1, pp. S5-S12.

[11] D. Jain, V. Singh, 2018."Feature selection and classification systems for chronic disease prediction: A review," Egypt. Inform. J., vol. 19, no.3, pp. 179-189.

[12] A. Williams, S. J.Kamper, J. H.Wiggers, K. M. O'Brien, H. Lee, L.Wolfenden, C. M.Williams, 2018. "Musculoskeletal conditions may increase the risk of chronic disease: a systematic review and meta-analysis of cohort studies," BMC medicine, vol. 16, no. 1, pp. 1-9.

[13] A. Khan, S.Uddin, U.Srinivasan, 2018. "Comorbidity network for chronic disease: A novel approach to understand type 2 diabetes progression," Int. J. Med. Inform., vol. 115, pp. 1-9.

[14] R. K.Naviaux, 2019. "Metabolic features and regulation of the healing cycles—A new model for chronic disease pathogenesis and treatment," Mitochondrion, vol. 46, pp. 278-297.

[15] J. Dekker, V. de Groot, 2018. "Psychological adjustment to chronic disease and rehabilitation–an exploration," Disabil. Rehabil., vol. 40, no.1, pp. 116-120.

[16] P. Brennan, M.Perola, G. J. van Ommen, E. Riboli, 2017. "Chronic disease research in Europe and the need for integrated population cohorts," Eur. J.Epidemiol., vol. 32, no. 9, pp. 741-749.

[17] H.Rheault, F. Coyer, L. Jones, A. Bonner, 2019. "Health literacy in Indigenous people with chronic disease living in remote Australia," BMC Health Serv. Res., vol. 19, no.1, pp. 1-10.

[18] G. R. Oates, B. E. Jackson, E. E. Partridge, K. P. Singh, M. N. Fouad, S. Bae, 2017. "Sociodemographic patterns of chronic disease: how the mid-south region compares to the rest of the country," Am. J. Prev. Med., vol. 52, no. 1, pp. S31-S39.

[19] L. Chen, A. Baird, D. Straub, 2019. "Fostering participant health knowledge and attitudes: An econometric study of a chronic disease-focused online health community," J.Manag. Inf. Syst., vol. 36, no.1, pp. 194-229.

[20] A.Sav, A.Salehi, F. S.Mair, S. S. McMillan, 2017. "Measuring the burden of treatment for chronic disease: implications of a scoping review of the literature," BMC Med. Res.Methodol., vol. 17, no.1, pp. 1-14.

[21] J. I.Mechanick, A. J. Garber, G.Grunberger., Y. Handelsman, W. T.Garvey, 2018. "Dysglycemia-based chronic disease: an American Association of Clinical Endocrinologists position statement," Endocr. Pract., vol. 24, no. 11, pp. 995-1011.

[22] F. H. Nielsen, 2018 "Dietary magnesium and chronic disease," Adv. Chronic Kidney Dis., vol. 25, no.3, pp. 230-23..

[23] A. G. E. M. de Boer, G. A.Geuskens, U.Bültmann., C. R.Boot, H.Wind, L. L.Koppes, M. H.Frings-Dresen, 2018. "Employment status transitions in employees with and without chronic disease in the Netherlands," Int. J. Public Health, vol. 63, no. 6, pp. 713-722.

[24] J. M. Nagata, K.Palar, H. C. Gooding, A. K. Garber, K. Bibbins-Domingo, S. D.Weiser, 2019. "Food insecurity and chronic disease in US young adults: findings from the National Longitudinal Study of Adolescent to Adult Health," J. Gen. Intern. Med., vol. 34, no. 12, pp. 2756-2762.

[25] M.Srinivas, P.Durgaprasadarao, V. Naga Prudhvi Raj, 2018. "Intelligent medicine box for medication management using IoT," 2018 2nd International Conference on Inventive Systems and Control (ICISC), IEEE.

[26] P.Arulanthu, E.Perumal, 2020. "An intelligent IoT with cloud centric medical decision support system for chronic kidney disease prediction," Int. J. Imaging Syst. Technol., vol. 30, no. 3, pp. 815-827.

[27] S. Gill, J. Hearn, G. Powell, E. Scheme, 2017. "Design of a multi-sensor IoT-enabled assistive device for discrete and deployable gait monitoring," 2017 IEEE Healthcare Innovations and Point of Care Technologies (HI-POCT), IEEE.

[28] D.Naranjo-Hernández, A.Talaminos-Barroso, J. R. Tosina, L. M. Roa, G. B. Rostan, P. C. Ramos, E. M. Martin, F. O. Ruiz, 2018. "Smart vest for respiratory rate monitoring of COPD patients based on non-contact capacitive sensing," Sensors, vol. 18, no.7.

[29] S. K.Sood, I.Mahajan, 2018. "IoT-fog-based healthcare framework to identify and control hypertension attack," IEEE Internet Things J., vol. 6, no.2,pp. 1920-1927.

[30] R.Ani, S. Krishna, N.Anju, M. S.Aslam, O. S. Deepa, 2017. "Iot based patient monitoring and diagnostic prediction tool using ensemble classifier," 2017 International Conference on Advances in Computing, Communications and Informatics (ICACCI), IEEE.
[31] J. Wan, M. A. A. H. Al-awlaqi, M. S. Li, M. O'Grady, X. Gu, J. Wang, N. Cao, 2018. "Wearable IoT enabled real-time health monitoring system," EURASIP J.Wirel.Commun.Netw., vol. 2018, no.1, pp. 1-10.
[32] A.Raji, P. G.Jeyasheeli, T.Jenitha, 2016. "IoT based classification of vital signs data for chronic disease monitoring," 2016 10th International Conference on Intelligent Systems and Control (ISCO), IEEE.
[33] A.Raji, P. K. Devi, P. G.Jeyaseeli, N. Balaganesh, 2016. "Respiratory monitoring system for asthma patients based on IoT," 2016 Online International Conference on Green Engineering and Technologies (IC-GET), IEEE.
[34] A. V.Radogna, P. A.Siciliano, S. Sabina, E.Sabato, S. Capone, 2020. "A low-cost breath analyzer module in domiciliary non-invasive mechanical ventilation for remote COPD patient monitoring," Sensors, vol. 20, no.3, pp. 653
[35] A. V.Radogna, N. Fiore, M. R.Tumolo, V. De Luca, 2019. "Exhaled breath monitoring during home ventilo-therapy in COPD patients by a new distributed tele-medicine system," J. Ambient Intell.Humaniz.Comput., pp. 1-9.
[36] F. Pitta, T.Troosters, M. A.Spruit, M.Decramer, R. Gosselink, 2005. "Activity monitoring for assessment of physical activities in daily life in patients with chronic obstructive pulmonary disease," Arch. Phys. Med. Rehabil., vol. 86, no.10, pp. 1979-1985.
[37] J. Zhang, Y. Song, C.Bai, 2013. "MIOTIC study: a prospective, multicenter, randomized study to evaluate the long-term efficacy of mobile phone-based Internet of Things in the management of patients with stable COPD," Int. J. Chron. Obstruct.Pulmon. Dis., vol. 8, pp. 433.
[38] T. T.Ho, T. Kim, W. J. Kim, C. H. Lee, K. J.Chae, S. H.Bak, S. O. Kwon, G. Y. Jin, E. K. Park, S. Choi, 2021. "A 3D-CNN model with CT-based parametric response mapping for classifying COPD subjects," Sci. Rep., vol. 11, no.1, pp. 1-12,
[39] P. K. D.Pramanik, B. K.Upadhyaya, S. Pal, T. Pal, 2019,."Internet of things, smart sensors, and pervasive systems: Enabling connected and pervasive healthcare," Healthcare Data Analytics and Management, Academic Press, pp. 1-58.
[40] A. S.Dhillon, S.Majumdar, M. St-Hilaire, 2018. "A mobile complex event processing system for remote patient monitoring," 2018 IEEE International Congress on Internet of Things (ICIOT), IEEE.
[41] J. Miranda, J. Cabral, S. R. Wagner, 2016. "An open platform for seamless sensor support in healthcare for the internet of things," Sensors, vol. 16, no.12, pp. 2089.
[42] A. Kumar, K.Abhishek, M. R.Ghalib, P. Nerurkar, K. Shah, M. Chandane, S. Bhirud, D. Patel, Y. Busnel, 2020. "Towards cough sound analysis using the Internet of things and deep learning for pulmonary disease prediction," Trans. Emerg. Telecommun. Technol., pp. e4184.
[43] J.Gubbi, R.Buyya, S.Marusic, M.Palaniswami, 2013 "Internet of Things (IoT): A vision, architectural elements, and future directions," Future Gener. Comput. Syst., vol. 29, no.7, pp. 1645-166..
[44] D. K. Ahern, I. M. Braun, M. E. Cooley, T. W.Bickmore, 2016. "Oncology informatics: behavioral and psychological sciences," Oncology informatics, Academic Press, pp. 231-251.
[45] M.Ramalatha, M.Alamelu, S.Kanagaraj, 2019. "Uncured Disease Rectification Using Net Collaborating Systems," Body Area Network Challenges and Solutions, Springer, Cham, pp. 19-36.
[46] J. Qi, P. Yang, A.Waraich, Z. Deng, Y. Zhao, Y. Yang, 2018. "Examining sensor-based physical activity recognition and monitoring for healthcare using Internet of Things: A systematic review," J. Biomed. Inform., vol. 87, pp. 138-153.

[47] A. A.AbdulGhaffar, S. M.Mostafa, A.Alsaleh, T. Sheltami, E. M. Shakshuki, 2020. "Internet of things based multiple disease monitoring and health improvement system," J. Ambient Intell.Humaniz.Comput., vol. 11, no.3, pp. 1021-1029.

[48] J. Qi, P. Yang, G. Min, O.Amft, F. Dong, L.Xu, 2017. "Advanced internet of things for personalised healthcare systems: A survey," Pervasive Mob.Comput., vol. 41, pp. 132-149.

[49] F.Sadoughi, A.Behmanesh, N.Sayfouri, 2020. "Internet of things in medicine: a systematic mapping study," J. Biomed. Inform., vol. 103, pp. 103383.

[50] J. C. Tsai, J. S.Leu, S. W.Prakosaet al., 2020. "Design and Implementation of an Internet of Healthcare Things System for Respiratory Diseases," Wirel. Pers. Commun., pp. 1-17.

[51] A. J.Jara, M. A. Zamora-Izquierdo, A. F. Skarmeta, 2013. "Interconnection framework for mHealth and remote monitoring based on the internet of things," IEEE J. Sel. Areas Commun., vol. 31, no.9, pp. 47-65.

[52] D. Ravì, C. Wong, B. Lo and G. Yang, 2017. "A Deep Learning Approach to on-Node Sensor Data Analytics for Mobile or Wearable Devices,"IEEE J. Biomed. Health Inform., vol. 21, no. 1, pp. 56-64.

[53] W. Y. Lin, V. K.Verma, M. Y. Lee, H. C. Lin, C. S. Lai, 2020. "Prediction of 30-Day Readmission for COPD Patients Using Accelerometer-Based Activity Monitoring," Sensors, vol. 20, no.1,pp. 217.

[54] Z.Alansari, S.Soomro, M. R. Belgaum,S. Shamshirband, 2018. "The rise of Internet of Things (IoT) in big healthcare data: review and open research issues," Progress in Advanced Computing and Intelligent Engineering, pp. 675-685.

[55] B. W.Hesse, N. K.Arora, W. Klein, 2016, "Communication science: connecting systems for health," Oncology informatics, Academic Press, pp. 253-275.

[56] Dal Mas, Francesca & Cobianchi, Lorenzo & Secundo, Giustina & Sousa, Maria & Rippa, Pierluigi. 2020. Technovation Special Issue Call for Papers "Digital Transformation in Healthcare and Medicine: Trends and Future Challenges". 10.13140/RG.2.2.20337.71526.

[57] A. R. Mori, M.Mazzeo, G.Mercurio, R.Verbicaro, 2013. "Holistic health: predicting our data future (from inter-operability among systems to co-operability among people)," Int. J. Med. Inform., vol. 82, no.4, pp. e14-e28.

[58] M. Merolli, K. Gray, F. Martin-Sanchez, 2013. "Health outcomes and related effects of using social media in chronic disease management: a literature review and analysis of affordances," J. Biomed. Inform., vol. 46, no. 6, pp. 957-969.

[59] C.Hudon, M. Fortin, J. Haggerty, C.Loignon, M. Lambert, M. E. Poitras, 2012. "Patient-centered care in chronic disease management: a thematic analysis of the literature in family medicine," Patient Educ.Couns., vol. 88, no.2, pp. 170-176.

[60] L. M. Hunt, N. H.Arar, 2001. "An analytical framework for contrasting patient and provider views of the process of chronic disease management," Med. Anthropol. Q., vol. 15, no.3, pp. 347-367.

[61] K. Gordon, F. Smith, S.Dhillon, 2007. "Effective chronic disease management: patients' perspectives on medication-related problems," Patient Educ.Couns., vol. 65, no.3, pp. 407-415.

[62] S. Kim, S. Kim, 2018. "User preference for an IoT healthcare application for lifestyle disease management," Telecommun. Policy, vol. 42, no.4, pp. 304-314.

[63] R. S. H.Istepanian, S. Hu, N. Y. Philip, A. Sungoor, 2011. "The potential of Internet of m-health Things "m-IoT" for non-invasive glucose level sensing.," 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, IEEE.

[64] B.Farahani, F.Firouzi, V. Chang, M.Badaroglu, N. Constant, K. Mankodiya, 2018. "Towards fog-driven IoT e-Health: Promises and challenges of IoT in medicine and healthcare," Future Gener. Comput. Syst., vol. 78, pp. 659-676.

[65] C. C.Bellos, A. Papadopoulos, R.Rosso,D. I. Fotiadis, 2014. "Identification of COPD Patients’ Health Status Using an Intelligent System in the CHRONIOUS Wearable Platform,"IEEE J. Biomed. Health Inform., vol. 18, no. 3, pp. 731–738.

[66] I.Chouvarda, N. Y. Philip, P.Natsiavas, 2014.“WELCOME—innovative integrated care platform using wearable sensing and smart cloud computing for COPD patients with comorbidities,” 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, IEEE.
[67] A. K. Prasad, 2021, “SMART asthma alert using IoT and predicting threshold values using decision tree classifier,” Applications of Internet of Things, Springer, Singapore, pp. 141-150.
[68] D. A. Rodríguez, A.Arbillagaet al., 2016. “Effects of interval and continuous exercise training on autonomic cardiac function in COPD patients,” ClinRespir J, vol. 10, no. 1, pp. 83-89.
[69] S.Anakal, P.Sandhya, 2019. “Low-cost IoT based spirometer device with silicon pressure sensor,” International Conference on Soft Computing and Signal Processing, Springer, Singapore.
[70] Y.Guo, X. Liu, S.Penget al., 2020. “A Review of Wearable and Unobtrusive Sensing Technologies for Chronic Disease Management,” Comput. Biol. Med., pp. 104163.
[71] S. L. Norris, R. E. Glasgow, M. M.Engelgau, P. J. Os’Connor, D.McCulloch, 2003. “Chronic disease management,” Disease Management & Health Outcomes,vol. 11, no.8, pp. 477-488.
[72] S. M. Dennis, N. Zwar, R. Griffiths, M. Roland, I. Hasan, G. Powell Davies, M.Harris, 2008. “Chronic disease management in primary care: from evidence to policy,” Med. J. Aust., vol. 188, pp. S53-S56.
[73] M.Hassanalieragh, A. Page, T.Soyata, G. Sharma, M. Aktas, G. Mateos, B. Kantarci, S. Andreescu, 2015,.“Health monitoring and management using Internet-of-Things (IoT) sensing with cloud-based processing: Opportunities and challenges,”In 2015 IEEE International Conference on Services Computing, IEEE, pp. 285-292.
[74] A.Gutte, R.Vadali, 2018. “IoT based health monitoring system using Raspberry Pi,”In 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA), IEEE, pp. 1-5.