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Diagnosing Chronic Obstructive Pulmonary Disease (COPD) Using Bayesian Belief Network

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Abstract:- Chronic Obstructive Pulmonary Disease (COPD) is a death-defying respiratory tract ailment that causes trouble in breathing which deteriorates after some time. COPD is an umbrella term used to order the amalgamation of Chronic Bronchitis and Emphysema. The manifestations of this infection are frequent coughing, fatigue, sweating, breathlessness, tiredness, weight loss, wheezing, fast heart rate, fast breathing and chest tightness just to name not many. This malady is pervasive with individuals whose age ranges from 30 or more and afterward arrives at its top in patients over 50. Because of the covering manifestations this malady imparts to other respiratory tract illnesses; it is in some cases under-analyzed and misdiagnosed a circumstance which is much uncontrolled in Sub-Sahara Africa. In time past, COPD has caused a large number of deaths overall yearly because of absence of early determination of the illness. In ongoing past, a few frameworks have been created to analyze this non-transmittable malady, yet they produced a ton of bogus negative during testing and couldn't identify COPD because of its covering side effects it imparts to other respiratory tract illnesses. Consequently, in this paper, we proposed and developed a model to foresee COPD utilizing an AI procedure called Bayesian Belief Network. The model was structured utilizing Bayes Server and tested with data gathered from COPD medical repository. The model had a general expectation precision of 99.98%; 99.79%, 95.91% and 98.39% sensitivity of COPD, Chronic Bronchitis and Emphysema in that order.

Keywords: Chronic Obstructive Pulmonary Disease, Chronic Bronchitis, Emphysema, Machine Learning, Bayesian Belief Network, Diagnosis.

1. Introduction

The human body is classified as a structure including numerous sorts of cells that commonly create tissues and afterward organ systems which are constrained by the biological systems resident in the body as expressed by [1]. Be that as it may, these biological systems inside the body controls the activity of organs in the human body which are required for day by day living, for example, circulatory system, digestive system, endocrine system, nervous system, reproductive system and respiratory system just to name a few. Of all the aforesaid systems, the respiratory system is a significant natural framework comprising of explicit organs liable for oxygen admission and ejection of carbon dioxide in a procedure called respiration. Besides, this respiratory system comprises of organs, for example, the trachea, the diaphragm and the lungs. Of the previously mentioned organs of the respiratory framework, Lungs are one of the human crucial organs liable for oxygen expulsion from the air we inhale thus moving it to our blood on the way to our cells and ejection of carbon dioxide when we breathe out. Regardless of the function of the respiratory framework in the human body, it is in danger of contaminations and sicknesses which can upset the usefulness of this framework, for example, chronic bronchitis, pneumonia, asthma, sarcoidosis, lung cancer, cystic fibrosis/bronchiectasis, pneumonia, pleural effusion, tuberculosis and chronic obstructive pulmonary disease infection and so on. Of the previously mentioned ailments, chronic obstructive pulmonary disease is the feared of all.

Chronic Obstructive Pulmonary Disease (COPD) is a dynamic hazardous lung infection that makes shortness of breath intensifications and genuine sickness as expressed by [2], it's anything but a solitary illness but instead an umbrella term used to depict the mix of chronic bronchitis and emphysema. The side effects of this illness are frequent coughing, fatigue, sweating, breathlessness, tiredness, weight loss, wheezing, fast heart rate, fast breathing and chest tightness just to name few.

In [3], it was expressed that emphysema is a sickness that gradually annihilates the air sacs in the lungs which ceaselessly meddle with the outward progression of air while chronic bronchitis is the irritation and narrowing of bronchial tubes which permits mucus to develop. All things considered, COPD isn't considered as an infectious malady rather it is categorized as a non-transmittable illness that is dynamic (generally deteriorates after some time) and an under-diagnosed life threatening lung ailment that may prompt passing if not diagnosed early and treated. In any case, there is no remedy for COPD, yet treatment can help ease indications, bring down the opportunity of complications and for the most part improve quality of life.

As indicated by [4], the pervasiveness of COPD globally in 2016 recorded more than 251 million cases. Likewise, it is assessed that 3.17 million deaths were brought about by the infection in 2015 (that is, 5% of all deaths universally in that year). Notwithstanding, over 90% of COPD deaths happen in low and middle-income nations of Africa.

In the investigation of [5], COPD was arranged as the fifth driving reason for death around the world, and is anticipated to turn into the third by 2020, outperforming the consolidated mortality for malaria, tuberculosis and HIV/AIDS in Africa.

In [6], it was accounted for that the prevalence of COPD in Africa extended from 4.1% to 24.8%, contingent upon which diagnostic criterion utilized. It was additionally expressed that improved diagnosis is the initial step to tending to COPD in Sub-Saharan Africa and that diagnosis and treatment is horribly deficient in this region.

In the investigation of [7], it was expressed that the ailment is predominant in individuals whose ages ranges from 30 to 40 and afterward arrives at its top in patients above 50.

According to [8], COPD is under-analyzed and misdiagnosed. This circumstance is much uncontrolled in Sub-Sahara Africa as after-effect of the trouble in differentiating this infection because of the overlapping symptoms with different illnesses, for example, Asthma, Tuberculosis just to give some examples which is one of its particular highlights.

Another upsetting feature of COPD is the fiery reaction in the airways and lung parenchyma which demonstrated that air routes of COPD patients are consistently aggravated and that the intensity of the inflammatory procedure supplements with the harm COPD causes to the lungs if not analyzed ahead of schedule as certified by [9].

Besides, analysis of COPD depends on manifestations which require arrangement of tests, for example, chest x-ray, sputum test, pulmonary function test, imaging tests, blood tests, lung function tests and spirometry test respectively. Of these tests, spirometry test is the most used of all.

Spirometry test is assessment which measures how profoundly an individual can inhale and how quick air can move into and out of the lungs. Moreover, a low pinnacle stream in the test outcome shows nearness of COPD, however may not be explicit to COPD in light of the fact that it very well may be brought about by other respiratory tract infections and lackluster showing during testing making the spirometry test not very compelling for diagnosing COPD.

However, Artificial Intelligence has been applied in diagnosing respiratory tract ailments in the works of [10], [11], [12], [13], [14], [15], [16], [17] and [18] in that order generated a ton of bogus negative during testing and couldn't recognize COPD viably because of the overlapping indications the illness imparts to other respiratory system diseases.

In this paper, we expect to apply a supervised AI strategy called Bayesian Belief Network (BBN) to analyze Chronic Obstructive Pulmonary Disease. BBN is a complex probabilistic network that joins expert information and observed datasets. It maps out circumstances and effects association among variables and encodes them with probability that connotes the amount where one variable is plausible to impact another. However, BBN was our method of choice on account of its ability to make prescient inference.

The strategy utilizes Bayes hypothesis which is a statistical formula that guides high accuracy in anticipating, distinguishing and diagnosing ailments. One noteworthy feature the proposed solution has over existing solutions is its capacity to diagnose COPD just as the overlapping symptoms this sickness has with other respiratory tract maladies which will bring forth improvement in the following areas: forecast of chronic obstructive pulmonary disease, detection of chronic obstructive pulmonary disease and diagnosis of respiratory tract infections with eventual outcomes identified with COPD.

However, the paper is organized as follows: Section I contains the introduction, Section II contains the related works on Chronic Obstructive Pulmonary Disease diagnosis using machine learning, Section III explains the chosen methodology utilized in diagnosing Chronic Obstructive Pulmonary Disease which is in this case, a supervised machine learning technique called Bayesian Belief Network, Section IV contains the simulation, results and discussion and Section V concludes research work with future directions.

2. Related Works

Zolnoori et al. [10] used fuzzy logic in classifying Fatal Asthma. The system results showcased a significant high recognition precision. Be that as it may, because of the covering side effects Asthma has with COPD and other lung maladies; it couldn't group the distinction in the system results delivered. Moreover, Fuzzy logic can't make bi-directional inferences.

Mary and Preethi [11] conducted an expansive overview of Computer-Aided Diagnosis System (CAD) for early identification of lung sickness. PC supported recognition methodologies were produced for early ailment discovery and treatment stages. However, the study results gave shifting outcomes dependent on the strategies utilized. Be that as it may, no system was actualized to distinguish lung illnesses, for example, COPD.

Sanchez-Morillo et al. [12] conducted a systematic audit directed on the utilization of prescient algorithms in-home observing of chronic obstructive pneumonic disease and asthma. The survey results of the algorithms utilized in home telemonitoring mediations in COPD and asthma advises the progress of prescient models with clinically valuable degrees of precision, affectability and particularity has not yet been accomplished. Notwithstanding, no framework was actualized rather the improvement of prescient models for the determination of lung maladies, for example, COPD and asthma and so forth was recommended

Gonzalez et al. [13] employed convolutional neural network (CNN) to recognize and stage chronic obstructive pulmonary disease (COPD) and predicted acute respiratory disease (ARD) events and mortality in smokers. The framework results demonstrated the capacity to foresee COPD with a significant level of discovery precision of 74.95%. By and by, the system network is time-consuming, the discovery nature hypothesis of why and how these deep architecture network is really absent what's more, they are computationally costly. Henceforth, there is the requirement for a quicker and more affordable method.

ShubhaDeepti et al. [14] used artificial neural network (ANN) to develop a medical expert framework for chronic respiratory infections analysis. The proposed framework exhibited the capacity to recognize ceaseless respiratory ailments with extremely high detection exactness more noteworthy than 90%; subsequently, demonstrating its helpfulness on the side of clinical diagnosis of respiratory diseases. Be that as it may, Neural Networks (NN) has the "black box" nature; it doesn't give a clue with regards to why what's more, how. Additionally, the system neural network is capital and time intensive and required a ton of information to execute appropriately during the learning procedure.

Badnjevic at al. [15] developed a specialist demonstrative framework to differentiate among patients with asthma, COPD dependent on estimations of lung capacity and data about patient's manifestations. The framework results exhibited the capacity of the expert indicative framework to effectively distinguish patients with asthma and COPD with a high discovery precision of 97%. Notwithstanding, the framework neglected to separate COPD from different maladies that have comparative covering side effects.

Braido et al. [16] designed an expert framework to analyze chronic obstructive lung disease (COLD). The framework results showed the capacity to determine COLD with a high identification precision of 94.7%. All things considered, expert systems have issue of information honesty, the development process of expert systems are time devouring and capital intensive; also it cannot perform bi-directional surmising on account of its particularity nature.

Abiyev et al. [17] utilized conventional neural network (CNN) for chest illnesses discovery. The framework obtained results showed the high recognition rate of chest infections in the proposed CNN with an identification exactness of 92.4%. Be that as it may, the system is very moderate and sets aside longer effort to push ahead and in reverse inside the network when the system is very profound as on account of the planned system, the hypothesis of why and how these profound design organize is really absent and they are computationally costly; it doesn't offer data about the overall significance of the different boundaries, it has less summing up execution issue, it has worry of showing up at local minimum and has over-fitting issues, the neural network convergence speed is generally moderate. Consequently, there is the requirement for a quicker and more affordable method.

Sathiya et al. [18] developed a Chronic Obstructive Pulmonary Disease in Computer Aided Diagnosis System utilizing conventional neural network (CNN). The framework results recognized COPD ailment from Computed Tomography images with a high discovery precision level. Be that as it may, NN requires a lot of information for approval, computationally costly, tedious and has the black box nature. It doesn't offer data about the overall significance of the different boundaries, it has less summing up execution issue; it has worry of showing up at local minimum and has over-fitting issues. Additionally, the neural network convergence speed is moderately moderate.

3. Methodology

Bayesian Belief Network (BBN) is a directed acyclic graphical model that utilizes probability (likelihood) to represent contingent conditions that prevails among nodes on a graph [19]. It is a complex probabilistic system that combines expert information and trial datasets. It designs out course of circumstances and effect association connections among variables and encodes them with likelihood that connotes the amount wherein one variable is plausible to influence another. Bayesian Belief Network depends on the Bayes hypothesis which depends on likelihood, which is represented in the mathematical equation below:

$$P(a|b) = \frac{P(b|a)P(a)}{P(b)} \qquad (1)$$

Where,
P(a) is the probability of event "a" happening without any information about event "b". It is called the "Prior". P(a/b) is the conditional probability of event "a" happening given that event "b" has already occurred. It is otherwise called the "Posterior". P(b/a) is the conditional probability of event "b" happening given that event "a" has already occurred. It is called the "Likelihood". P(b) is the probability of event "b" happening without any information about event "a". It is called the "Marginal Likelihood". The Naive Bayes classifiers are often represented as a type of directed acyclic graph (DAG). The Directed Acyclic Graph (DAG) comprises of vertices representing random variables and arrows connecting pairs of nodes.

Figure 1 shows a pictorial portrayal of a Bayesian Belief Network.

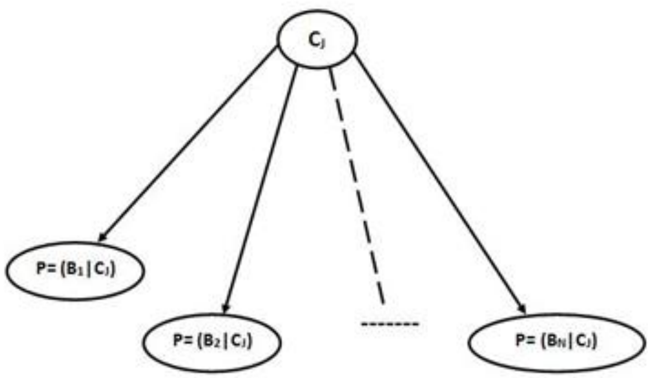

Figure 1: A Pictorial Representation of a Bayesian Belief Network

A few points of interest of this model are: it is very brisk in making inferences, the resulting probabilities are anything but easy to decipher, the learning algorithm is very straightforward and the model satisfactorily joins with utility functions to make optimal inferences. In this paper, we plan to recognize Chronic Obstructive Pulmonary Disease (COPD) and its side effects utilizing a managed AI procedure called Bayesian Belief Network (BBN).

A model comprising of 58 nodes where a few nodes speak to a type of malady infirmity or elements that impact finding of COPD and its side effects will be structured utilizing Bayes Server. A COPD dataset will be utilized to prepare and test the system. Utilizing the Pareto Principle, 80% of the dataset will be utilized to prepare the model while the remainder will be employed in testing the model. The point of the model is to accomplish a significant level of identification exactness with the utilization of the covering indications of COPD.

4. Results and Discussion

The simulation was led utilizing a COPD dataset in training, testing and foreseeing Chronic Obstructive Pulmonary Disease (COPD) which was recuperated from [20]. Besides, previews of used dataset, designed BBN model for identifying COPD and its manifestations, BBN model convergence chart, loglikelihood batch query chart, feature importance of nodes chart, in-sample detection chart, likelihood plots of diseases causing COPD, loglikelihood graph for detecting COPD and likelihood against loglikelihood plot for predicting COPD were taken during the simulation procedure which are appeared beneath in figures 2, 3, 4, 5, 6, 7, 8,9,10,11 and 12 respectively with the results discussed underneath the diagrams. Then again, the used dataset include mix of ailment tribulations and parts thought about in the recognition of COPD signifying 58 with each sickness and factor having a value which addresses the probability of such ailment malady and factor causing COPD.

The sicknesses and components are: Age > 40, Antibiotics for Exacerbation, Asthma-COPD Overlap Syndrome (ACOS), Asymptomatic, Bluish Tinge, Breathlessness, Bronchodilator Reversibility, Chemicals, Chest Tightness, Chills, Clear, Chronically Normal, Chronic Bronchitis, Critical, COPD, Common, Dyspnea, Early Morning, Emphysema, Excessive Phlegm, Family History, Fast Breathing, Fast Heart Rate, Fatigue, Frequent Coughing, Good Efficacy, Green Colour, Heating Fuel Smoke, History of Atopy, Home Cooking Smoke, Hypoxema, IgE Elevation, Intermittent, Leukotriene Modifier Responsiveness, Lower Muscle Endurance, Mild, Moderate, Occupational Dusts, Partial, Persistent, Polycythemia, Productive, Progressive, Progressive Deterioration, Severe, Slight Fever, Smoke History, Steroid Responsiveness, Sweating, Tiredness, Typical, Tobacco Smoke>=10 Pack Years, Uncommon, Unproductive, Weak, Weight Loss, Wheezing, Whitish Colour and Yellowish-Gray Colour respectively.

Figure 2 below shows a snapshot of the dataset utilized in training, testing and predicting Chronic Obstructive Pulmonary Disease.

Clear	COPD	Critical	Dyspnea	Early Morning	Emphysema	Excessive
2.15	0.24	0.704	1.34	-0.0953	-0.238	-0.873
2.09	-0.523	1.16	-0.787	0.214	-1.23	0.0126
1.5	-0.0792	-1.78	0.931	0.0469	0.37	-1.56
1.47	-2.02	-1.43	0.164	-0.223	-0.998	1.16
1.46	1.46	-0.125	-0.361	0.408	0.863	-0.497
1.42	-1.07	-0.35	0.273	0.82	-1.52	0.992
1.17	1.43	0.979	-0.845	0.102	0.73	-0.978
1.06	0.481	0.406	0.857	-0.646	-0.152	0.521
0.903	0.303	0.189	0.502	0.258	0.108	0.281
0.806	-1.76	1.97	1.14	-0.482	-1.92	1.18
0.741	0.817	-0.291	0.471	-0.512	1.02	-1.59
0.733	-1.36	-0.149	0.116	1.13	0.962	-0.752
0.624	0.269	-0.483	-0.407	-0.0104	-1.78	0.499
0.478	0.638	-0.993	-1.34	-1.09	-0.123	-1.11
0.334	-0.233	-1.35	0.241	-0.658	2.14	0.371
0.324	-0.16	-0.134	1.92	-1.49	-0.374	0.628
0.233	0.231	0.305	-0.336	0.0107	-0.426	-1.6
0.161	-1.01	-1.23	-0.545	0.309	0.461	-0.286
0.138	0.532	-0.572	-0.896	-0.252	-2.49	0.139
0.0504	-0.169	1.95	-0.399	-0.584	-0.373	0.0121
0.00...	-1.33	0.971	0.946	-0.54	1.23	-0.471
-0.0...	-2.12	0.422	-0.16	-0.383	1.31	0.291
-0.0...	0.0612	-3.11	-0.797	-0.1	-1.06	0.63
-0.11	-0.12	-1.39	-0.286	-0.0276	1.44	0.235

Figure 2: Snapshot of Dataset

The Bayesian Belief Network model was planned utilizing Bayes-Server stage. The Bayesian Belief Network (BBN) for foreseeing Chronic Obstructive Pulmonary Disease (COPD) was structured with the end goal that the nodes on the network are connected dependent on the likelihood of a sickness affliction coming about to another and factor affecting another factor. In our model for a case to be meant as a COPD case. The sicknesses, infection causing specialists and different components taken into awareness in the analysis of COPD are Age > 40, Antibiotics for Exacerbation, Asthma-COPD Overlap Syndrome (ACOS), Asymptomatic, Bluish Tinge, Breathlessness, Bronchodilator Reversibility, Chemicals, Chest Tightness, Chills, Clear, Chronically Normal, Chronic Bronchitis, Critical, COPD, Common, Dyspnea, Early Morning, Emphysema, Excessive Phlegm, Family History, Fast Breathing, Fast Heart Rate, Fatigue, Frequent Coughing, Good Efficacy, Green Colour, Heating Fuel Smoke, History of Atopy, Home Cooking Smoke, Hypoxema, IgE Elevation, Intermittent, Leukotriene Modifier Responsiveness, Lower Muscle Endurance, Mild, Moderate, Occupational Dusts, Partial, Persistent, Polycythemia, Productive, Progressive, Progressive Deterioration, Severe, Slight Fever, Smoke History, Steroid Responsiveness, Sweating, Tiredness, Typical, Tobacco Smoke>=10 Pack Years, Uncommon, Unproductive, Weak, Weight Loss, Wheezing, Whitish Colour and Yellowish-Gray Colour respectively.

Figure 3 shows the BBN model for detecting Chronic Obstructive Pulmonary Disease (COPD), its symptoms.

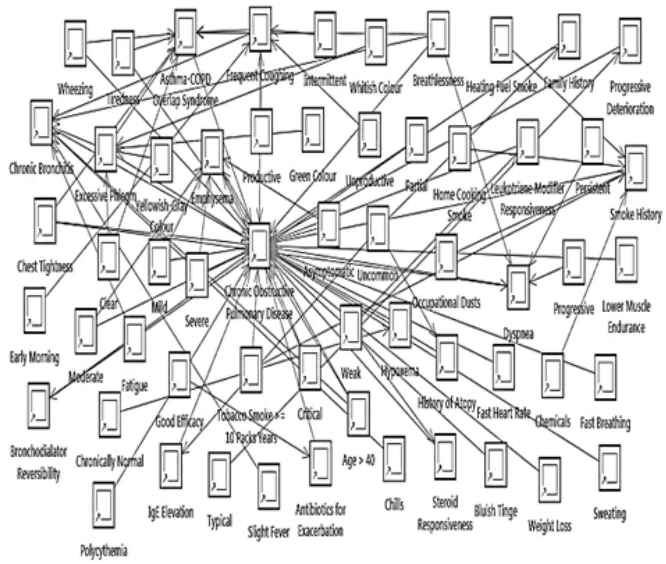

Figure 3: Bayesian Belief Network Model for Detecting Chronic Obstructive Pulmonary Disease (COPD) With Its Symptoms.

So, to mathematically represent our model we have:

$$\text{Chronic Obstructive Pulmonary Disease}(\text{COPD}) = \prod_{i=1}^{58} P(\text{Disease}_i | \text{Parents}(\text{Disease}_i)) \quad (2)$$

Where, Disease: Node with a Disease Ailment

Parents (Disease_i) = Nodes that converge on Disease $\text{Ailment}_{i..}$ The dataset was used to train and test the model. Upon completion of training and testing the BBN model, the test data converged at time series 2. The log likelihood value for each case was recorded. Figure 4 shows the BBN model convergence of Chronic Obstructive Pulmonary Disease (COPD) and its symptoms at Iteration Count 2.

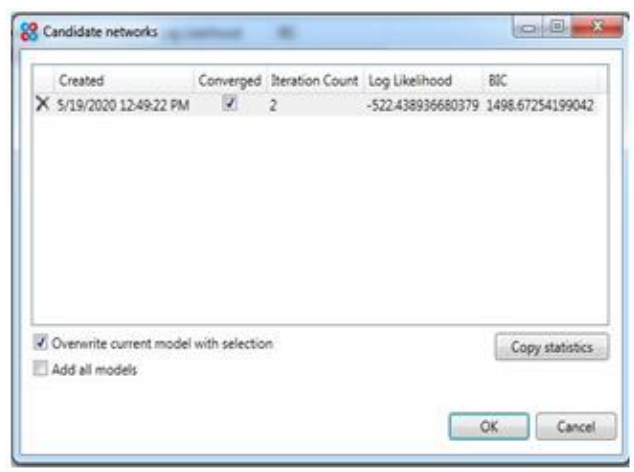

Figure 4: Bayesian Belief Network Model for Detecting Chronic Obstructive Pulmonary Disease (COPD) Converging at Time Series 2.

Figures 5, 6, 7, 8, 9, 10, 11 and 12 shows log likelihood batch query chart for predicting COPD with its symptoms, feature importance chart of nodes in the BBN model, the in-sample anomaly detection chart, the likelihood plot showing relation of Chronic Bronchitis leading to a COPD infection case and its probabilities, the likelihood plot showing relation of Emphysema leading to a COPD infection case and its probabilities, the likelihood plot showing relation of Chronic Bronchitis and Emphysema combined leading to a Chronic Obstructive Pulmonary Disease (COPD) Infection Case and its probabilities and the loglikelihood graph for detecting COPD with its symptoms and likelihood against loglikelihood for predicting Chronic Obstructive Pulmonary Disease with its symptoms respectively. The results generated from the simulation demonstrated that the system had the option to anticipate 99% COPD on the dataset precisely and it had a loglikelihood of 66.50 on the test dataset.

The figure 5 below shows the loglikelihood batch query chart for predicting Chronic Obstructive Pulmonary Disease (COPD*)* with its symptoms.

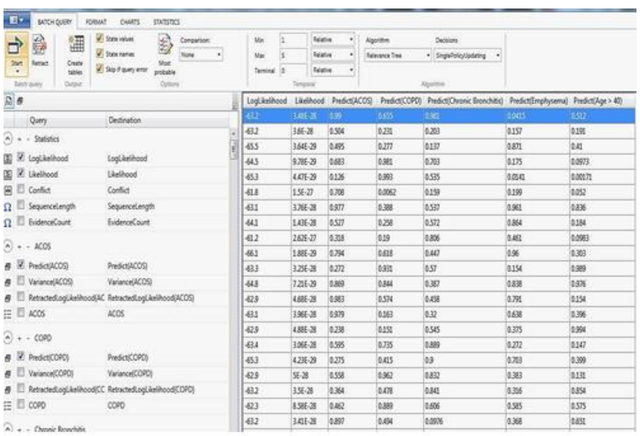

Figure 5: The Loglikelihood Batch Query Chart for Predicting Chronic Obstructive Pulmonary Disease with Its Symptoms.

This loglikelihood chart batch shows the outcome of the test data. Here, 50 exploratory cases were directed and the investigation of the outcome produced from the test data is demonstrated as follows:

In Experiment 1: The estimation of Predict(ACOS) was 0.99 contrasted with 0.99012944,Predict (COPD) was 0.655 contrasted with 0.65482056, Predict(Chronic Bronchitis) was 0.981 contrasted with 0.981017172, Predict(Emphysema) was 0.00415 contrasted with 0.00414755 and Predict(Age > 40) was 0.512 contrasted with 0.511843549 in Experiment 1.

In Experiment 2: The estimation of Predict(ACOS) was 0.504 contrasted with 0. 503830292, Predict(COPD) was 0.231 contrasted with 0.2310409202, Predict(Chronic Bronchitis) was 0.203 contrasted with 0.2028237832, Predict(Emphysema) was 0.157 contrasted with 0.1570106025, Predict(Age > 40) was 0.191 contrasted with 0.190603266 in Experiment 2.

In Experiment 3: The estimation of Predict(ACOS) was 0.495 contrasted with 0.49503496, Predict (COPD) was 0.277 contrasted with 0.277001181, Predict(Chronic Bronchitis) was 0.137 contrasted with 0.137001923, Predict(Emphysema) was 0.871 contrasted with 0.8705788692 and Predict(Age > 40) was 0.41 contrasted with 0.4050433 in Experiment 3.

Besides, this investigation proceeds up to Experiment number 50. Henceforth, the system results demonstrated a 0.326 worth distinction between the forecast outcomes and unique test data of 100% coming about to 99% expectation exactness.

Figure 6 below shows the feature importance chart for nodes in the BBN model.

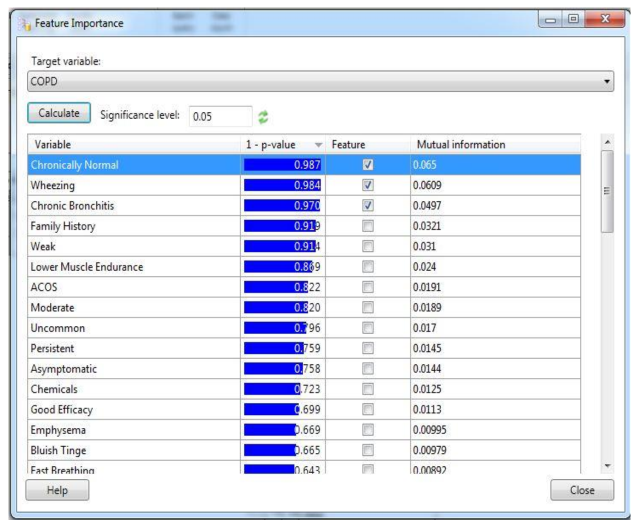

Figure 6: The Feature Importance Chart for Nodes in the BBN Model

The Feature Importance Chart shows p-value of the variable (nodes), Feature and Mutual information regarding the Chronic Obstructive Pulmonary Disease (COPD) Node. The p-value connotes the probability (likelihood) of the nodes being the reason for a COPD disease. The Feature box is checked if that specific node is completely associated with the reason for a COPD infection. The Mutual Information shows the relationship with nodes straightforwardly associated with each other (for example for this situation the immediate relationship of the nodes with the COPD) and allotted a value.

The Significance Level implies the margin error in the recognition of COPD and its side effects.

The figure 7 below shows the in-sample anomaly detection chart for the Bayesian Belief Network Model.

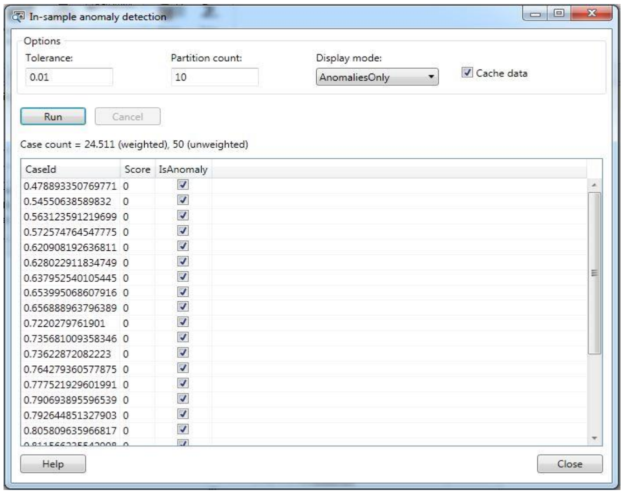

Figure 7: The In-Sample Anomaly Detection Chart Chart for Nodes in the BBN Model.

The In-sample Anomaly Detection Chart shows 50 exploratory consequences of recognizing Chronic Obstructive Pulmonary Disease (COPD). Each Case is assigned an ID (Identification esteem) which is the estimation of the Predict(COPD) in Figure 5 above. The IsAnomaly checkbox is checked to distinguish that each case is an affirmed instance of Chronic Obstructive Pulmonary Disease contamination. The 50 instances of COPD has a case tally estimation of 24.511 (weighted) which implies the significance of the cases prompting a COPD disease and 50 case tally esteem connotes the quantity of cases in the pool of information accessible to the system for identification of COPD in the dataset pool. The resilience is the room for give and take that could be encountered as respects to the recognition of the COPD and its manifestations.

The figure 8 below shows the likelihood plot showing relation of Chronic Bronchitis leading to a Chronic Obstructive Pulmonary Disease (COPD) infection case and its probabilities.

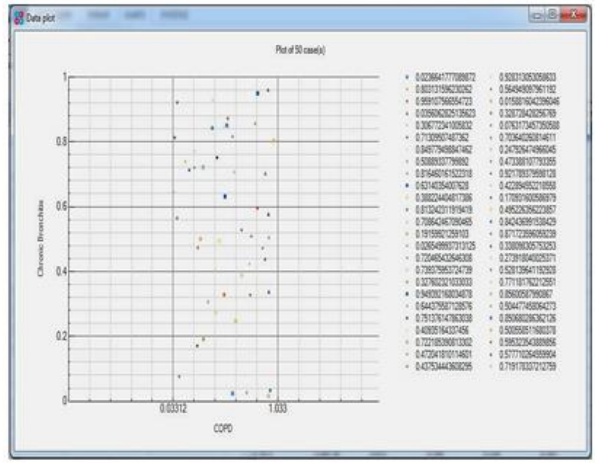

Figure 8: The Likelihood Plot Showing Relation of Chronic Bronchitis Leading to a Chronic Obstructive Pulmonary Disease (COPD) Infection Case And Its Probabilities In The BBN Model

The probability plot shows the chance of how contact with Chronic Bronchitis drives a Chronic Obstructive Pulmonary Disease (COPD) contamination case. In this plot, 50 test cases were thought about with each hued point in the diagram named a case and appointed a likelihood which is positioned on the right of the chart. The Chronic Bronchitis on the Y-axis is plotted against Chronic Obstructive Pulmonary Disease (COPD) on the X-axis.

Be that as it may, from this chart, there are five analytic classes of COPD cases which our system had the option to recognize; they are asymptomatic, mild, moderate, serious, and critical classes individually. Asymptomatic Class: This class ranges from 0 to 0.2 on Y-axis and 0.03312 to 1.033 on X-axis. This area has 7 hued focuses (cases). This implies the 7 coloured points in this locale speak to 7 instances of no Chronic Bronchitis disease at all, subsequently this class of patients is ordered as being Asymptomatic.

Mild Class: This class ranges from 0.2 to 0.4 on Y-axis and 0.03312 to 1.033 on X-axis. This area has 7 hued focuses (cases). This implies the 7 tinted focuses in this area speak to 7 instances of patients with Chronic Bronchitis contamination with the seriousness level classified as being Mild.

Moderate Class: This class ranges from 0.4 to 0.6 on Y-axis and 0.03312 to 1.033 on X-axis. This area has 13 hued focuses (cases).This implies that the 13 hued focuses in this locale speak to 13 instances of patients with Chronic Bronchitis contagion with the seriousness level classified as being Moderate.

 https://doi.org/10.22362/ijcert/2020/v7/i05/v7i0503

Severe Case: This class ranges from 0.6 to 0.8 on Y-axis and 0.03312 to 1.033 on X-axis. This locale has 12 hued focuses (cases). This means the 12 shaded focuses in this locale speak to 12 instances of patients with Chronic Bronchitis infectivity with the seriousness level arranged as being Severe.

Critical Class: This level reaches from 0.8 to 1 on Y-axis and 0.03312 to 1.033 on X-axis. This district has 11 hued focuses (cases). This implies the 11 hued focuses in this area speak to 11 instances of patients with Chronic Bronchitis disease with the seriousness level sorted as being Critical. All the 50 cases in figure 8 had likelihood esteem less than 1; with the most noteworthy likelihood estimation of Chronic Bronchitis causing a COPD contamination answered to be 0.959107566554723 which is under 1. Of the 50 trial cases, the system anticipated 50 instances of Chronic Bronchitis prompting COPD case going from asymptomatic, mild, moderate, severe, and critical classes accurately from the test data with 95.91% sensitivity of Chronic Bronchitis disease.

Figure 9 below shows the likelihood plot showing relation of Emphysema leading to a Chronic Obstructive Pulmonary Disease (COPD) infection case and its probabilities.

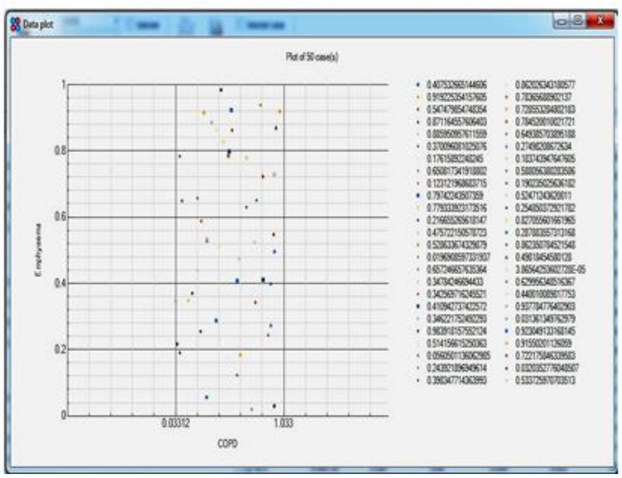

Figure 9: The Likelihood Plot Showing Relation of Emphysema Leading to a Chronic Obstructive Pulmonary Disease (COPD) Infection Case And Its Probabilities In The BBN Model

The probability plot shows the chance of how contact with Emphysema drives a Chronic Obstructive Pulmonary Disease (COPD) contamination case. In this plot, 50 exploratory cases were contemplated with each hued point in the diagram delegated a case and allotted a likelihood which is positioned on the privilege of the chart. The Emphysema on the Y-axis is plotted against Chronic Obstructive Pulmonary Disease (COPD) on the X-axis. Be that as it may, from this diagram, there are five demonstrative classes of COPD cases which our framework had the option to distinguish; they are asymptomatic, mild, moderate, severe, and critical classes separately.

Asymptomatic Class: This class ranges from 0 to 0.2 on Y-axis and 0.03312 to 1.033 on X-axis. This district has 7 hued focuses (cases). This means the 7 hued focuses in this district speak to 7 instances of no Emphysema disease at all, subsequently this classification of patients are arranged as being Asymptomatic.

Mild Class: This class ranges from 0.2 to 0.4 on Y-axis and 0.03312 to 1.033 on X-axis. This district has 10 shaded focuses (cases). This implies the 10 hued focuses in this district speak to 10 instances of patients with Emphysema disease with the seriousness level ordered as being Mild.

Moderate Class: This class ranges from 0.4 to 0.6 on Y-axis and 0.03312 to 1.033 on X-axis. This district has 13 shaded focuses (cases).This implies that the 13 hued focuses in this locale speak to 13 instances of patients with Emphysema disease with the seriousness level ordered as being Moderate.

Serious Case: This class ranges from 0.6 to 0.8 on Y-axis and 0.03312 to 1.033 on X-axis. This locale has 10 shaded focuses (cases). This implies the 10 hued focuses in this locale speak to 10 instances of patients with Emphysema disease with the seriousness level sorted as being Severe.

Critical Class: this level extent from 0.8 to 1 on Y-axis and 0.03312 to 1.033 on X-axis. This district has 10 hued focuses (cases). This connotes the 10 shaded focuses in this district speak to 10 instances of patients with Emphysema contamination with the seriousness level sorted as being Critical.

All the 50 cases in figure 11 had likelihood esteem less than 1; with the most noteworthy likelihood estimation of Emphysema causing a COPD contamination answered to be 0.983918157552124 which less than 1. Of the 50 test cases, the system anticipated 50 instances of Emphysema prompting a COPD case going from asymptomatic, mild, moderate, serious, and critical classes effectively from the test data with 98.39% sensitivity of Emphysema infectivity.

Figure 10 beneath shows the probability plot indicating connection of Chronic Bronchitis and Emphysema consolidated prompting a Chronic Obstructive Pulmonary Disease (COPD) infection case and its probabilities.

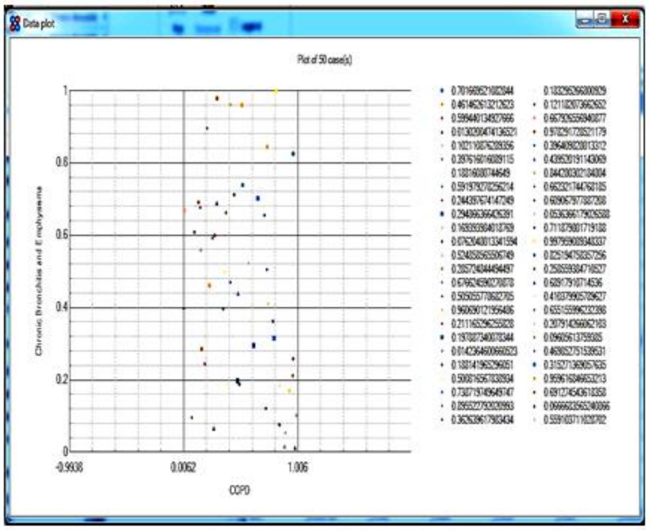

Figure 10: The Likelihood Plot Showing Relation of Chronic Bronchitis and Emphysema Joined Leading To A Chronic Obstructive Pulmonary Disease (COPD) Infection Case And Its Probabilities In The BBN Model

The probability plot shows the chance of how contact with Chronic Bronchitis and Emphysema drives a Chronic Obstructive Pulmonary Disease (COPD) contamination case. In this plot, 50 trial cases were contemplated with each shaded point in the chart delegated a case and doled out a likelihood which is positioned on the privilege of the diagram. The Chronic Bronchitis and Emphysema on the Y-axis is plotted against Chronic Obstructive Pulmonary Disease (COPD) on the X-axis. In any case, from this diagram, there are five demonstrative classes of COPD cases which our system had the option to recognize; they are asymptomatic, mild, moderate, serious, and critical classes separately.

Asymptomatic Class: This class ranges from 0 to 0.2 on Y-axis and 0.0062 to 1.006 on X-axis. This area has 13 shaded focuses (cases). This implies the 13 hued focuses in this district speak to 13 joined instances of no Chronic Bronchitis and Emphysema disease at all; henceforth this class of patients is classified as being Asymptomatic.

Mild Class: This class ranges from 0.2 to 0.4 on Y-axis and 0.0062 to 1.006 on X-axis. This district has 10 shaded focuses (cases). This connotes the 10 shaded focuses in this district speak to 10 instances of patients with consolidated instances of Chronic Bronchitis and Emphysema with the seriousness level classified as being Mild.

Moderate Class: This class ranges from 0.4 to 0.6 on Y-axis and 0.0062 to 1.006 on X-axis. This district has 10 shaded focuses (cases).This implies that the 10 hued focuses in this locale speak to 10 joined instances of Chronic Bronchitis and Emphysema with the seriousness level arranged as being Moderate.

Severe Case: This class ranges from 0.6 to 0.8 on Y-axis and 0.0062 to 1.006 on X-axis. This area has 10 shaded focuses (cases). This means the 10 shaded focuses in this district speak to consolidated instances of Chronic Bronchitis and Emphysema with the seriousness level arranged as being Severe.

Critical Class: This level reaches from 0.8 to 1 on Y-axis and 0.0062 to 1.006 on X-axis. This locale has 7 shaded focuses (cases). This implies the 7 hued focuses in this area speak to 7 joined instances of Chronic Bronchitis and Emphysema disease with the seriousness level arranged as being Critical.

All the 50 cases in figure 10 had likelihood esteem less than 1; with the most elevated likelihood estimation of Chronic Bronchitis and Emphysema causing a COPD Infection answered to be 0.9979590893483337 which is under 1. Of the 50 exploratory cases, the framework anticipated 50 instances of Chronic Bronchitis and Emphysema prompting a COPD case running from asymptomatic, mild, moderate, serious, and critical classes effectively from the test data with 99.79% sensitivity of consolidated Chronic Bronchitis and Emphysema infection.

The figure 11 shows the Loglikelihood Graph for Detecting Chronic Obstructive Pulmonary Disease (COPD) with its symptoms.

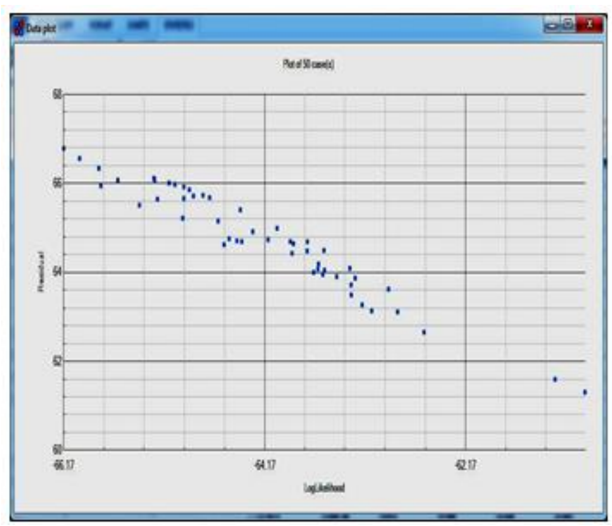

Figure 11: The Loglikelihood Graph for Detecting Chronic Obstructive Pulmonary Disease (COPD) with its Symptoms

This loglikelihood graph for recognizing COPD shows residual values on the vertical axis plotted against the loglikelihood esteems on the even axis which are free factors.

A residual esteem is a proportion of how much a regression line vertically misses a data point. Regression lines are the best attack of a lot of data. The lines are ordered as midpoints; a couple of data points focuses will fit the line and others will miss. In this chart, it shows that 50 trial cases brought about estimation of 66.50, 66.35, 66.23, 66.10, 66.09, 66.05…., and 61.25 respectively. Preferably, residual values ought to be similarly and arbitrarily separated around the level lines. Taking a perspective on the system' exploratory outcomes esteems acquired from the even lines on the diagram, it very well may be seen that where the most elevated residual value and the loglikelihood free factor achieved meets at - 66.17 on the level line with 68 being the most noteworthy worth that can be reached on the vertical line.

The residual esteem achieved is 66.50 and loglikelihood independent value is - 66.17, the distinction between the two qualities is 0.33 which is the contrast between the estimations of the forecast outcomes and unique test data of 100% in figure 5. Hence, the Loglikelihood value of distinguishing Chronic Obstructive Pulmonary Disease (COPD) with its Symptoms is 66.50.

Figure 12 shows the likelihood against loglikelihood for anticipating Chronic Obstructive Pulmonary Disease (COPD) with its indications.

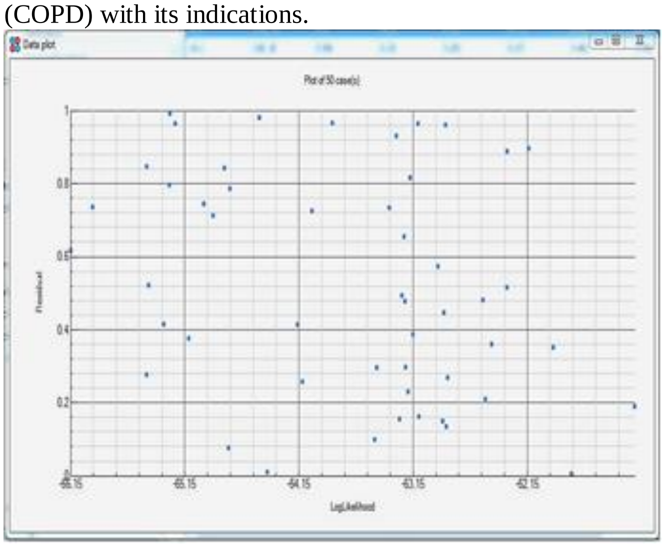

Figure 12: The Likelihood against the Loglikelihood Graph for Predicting Chronic Obstructive Pulmonary Disease with its Symptoms

This likelihood against loglikelihood plot for predicting Chronic Obstructive Pulmonary Disease shows the rest of the likelihood (Probability) on the vertical axis plotted against the Loglikelihood regards on the even axis which are free factors. A residual (Likelihood) value is an assessment of how much a relapse line vertically misses a data point. It shows up the probability of an event (Chronic Obstructive Pulmonary Disease) occurring with the probabilistic values some place in the scope of 0 and 1.

Regression lines are the champion assault of a ton of data. The lines are appointed ordinary with two or three data points fitting the line while others miss the line. In this outline, 50 exploratory cases were coordinated which realized the estimations of 0.9998, 0.9996, 0.9995, 0.9994, 0.8995, 0.8950…., up to 0.0002 respectively. Ideally, 0.8995, 0.8950…….. Furthermore, 0.0002 individually. Ideally, residual (probability) values should be consistently and aimlessly scattered around the level lines. Essentially, viewing the framework' preliminary outcomes regards obtained from the level lines on the graph, it tends to be seen that the residual likelihood value got is 0.9998 and log likelihood independent esteem is - 66.15.

Consequently, in this system, the most significant probability value that can be accomplished is 1. With 1, being the 100 % residual (likelihood) percentage mark, to get our forecast precision percentage, we segment gained probability likelihood value by most essential probability esteem that can be cultivated and increment by most imperative remaining residual mark, that is 0.9998/1*100% = 99.98% forecast exactness rate on the test data. Besides, the likelihood plots brings about figure 8,9 and 10 above indicated all classes of seriousness status of Chronic Bronchitis, Emphysema; Chronic Bronchitis and Emphysema joined contamination cases driving COPD running from asymptomatic, mild, moderate, severe, and critical classes respectively with their probabilities while figure 11 showed the system loglikelihood estimation of 66.50 for recognizing Chronic Obstructive Pulmonary Disease and its signs while the likelihood against loglikelihood desire graph of Chronic Obstructive Pulmonary Disease and its reactions in figure 12 demonstrated the 99.98% precision accuracy of the system.

In this way, the likelihood of having consolidated Chronic Bronchitis and Emphysema and given there is proof of different infirmities and elements that impact determination of the aforementioned illnesses prompting COPD is meant as: P(COPD | Age > 40, Antibiotics for Exacerbation, Asthma-COPD Overlap Syndrome (ACOS), Asymptomatic, Bluish Tinge, Breathlessness, Bronchodilator Reversibility, Chemicals, Chest Tightness, Chills, Clear, Chronically Normal, Chronic Bronchitis, Critical, COPD, Common, Dyspnea, Early Morning, Emphysema, Excessive Phlegm, Family History, Fast Breathing, Fast Heart Rate, Fatigue, Frequent Coughing, Good Efficacy, Green Colour, Heating Fuel Smoke, History of Atopy, Home Cooking Smoke, Hypoxema, IgE Elevation, Intermittent, Leukotriene Modifier Responsiveness, Lower Muscle Endurance, Mild, Moderate, Occupational Dusts, Partial, Persistent, Polycythemia, Productive, Progressive, Progressive Deterioration, Severe, Slight Fever, Smoke History, Steroid Responsiveness, Sweating, Tiredness, Typical, Tobacco Smoke>=10 Pack Years, Uncommon, Unproductive, Weak, Weight Loss, Wheezing, Whitish Colour and Yellowish-Gray Colour) = 0.997959089348337.

From the test, it tends to be seen that our model has a higher residual loglikelihood esteem which is 66.50, overall forecast exactness of 99.98%; 99.79%, 95.91% and 98.39% sensitivity of COPD, Chronic Bronchitis and Emphysema in that order. At long last, contrasting the 99.98% forecast exactness of our model with the trials directed by [13, 14, 15, 16 and 17] which has 74.95%, 91%, 97%, 94.7% and 92.4% expectation precision respectively, it is clear our model has a superior expectation precision. The higher expectation exactness accomplished by our model could be because of the scope of the dataset utilized in preparing and testing the model just as its capacity to anticipate the covering side effects Chronic Obstructive Pulmonary Disease (COPD) shares with other respiratory tract illnesses, henceforth helping the high recognition precision of the aforementioned ailment.

5. Conclusion and Future Scope

Chronic Obstructive Pulmonary Disease (COPD) is a life threatening illness that is very hard to distinguish because of the covering side effects the ailment imparts to other respiratory tract maladies. In ongoing past, a few strategies have been utilized in identifying COPD with the sole point of diminishing less than ideal passings of patients because of absence of early finding of the aforementioned infection which clinical experts are endeavouring to enhance.

In this paper, we used a managed AI procedure called Bayesian Belief Network to anticipate Chronic Obstructive Pulmonary Disease (COPD) and its manifestations. The system had 58 nodes with every node speaking to a select illness and factors that impact determination of COPD. The model was trained and tested and had a general precision of 99.98% in foreseeing Chronic Obstructive Pulmonary Disease with its side effects; with 99.79%, 95.91% and 98.39% sensitivity of COPD, Chronic Bronchitis and Emphysema in that exact order.

We can deduce that the results showcased the model's learning ability, regardless of the fact that the data utilized can be improved enormously, particularly for the figure of outbreaks of the chronic obstructive pulmonary disease aside from that in this study we focused on overlapping symptoms. However, the proposed model relied on the precision of the expectation of infected cases during the analysis stage.

For future works, there is need to include more data influenced by the sickness in other to improve the prescient and get optimal outcomes which will be used and realize improvement in the following areas: forecast of chronic obstructive pulmonary disease and identification of chronic obstructive pulmonary disease.

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