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A Supervised Machine Learning Model for Early Detection of Epilepsy and Seizure Disorders Based On Observed Side-Effects

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Abstract

Epilepsy is a neurological disorder that is persistent and characterized by uncontrolled seizure which influences individuals in respective of age and sex, with the human brain being the major spot where it is instigated without any evidence of the cause of trigger, hence affecting any part of the body. Owing to its paroxysmal nature which has affected more than 50 million individuals globally, the World Health Organization categorized epilepsy as a major and most universal neurological disease worldwide with 80% of these infected individuals living in low and middle-income countries of Sub-Sahara Africa. Even so, in the recent past, several systems have been developed to detect this non-communicable ailment, yet they delivered a ton of bogus negative during testing and couldn't distinguish epilepsy because of the overlapping symptoms it imparts to other seizure disorders. Hence, in this paper, we proposed and built up a model to predict epilepsy and seizure disorders using an AI technique called Bayesian Belief Network. The model was structured using Bayes-Server and tested with data retrieved from the epilepsy machine learning repository. The model had an overall prediction exactness of 99.98%; 99.65% and 99.45% sensitivity of epilepsy and seizure disorders in that order.

Keywords: *Epilepsy; Seizure Disorders; Prediction; Detection; Artificial Intelligence, Supervised Machine Learning; Bayesian Belief Network.*

1. Introduction

The human body is a biological system that comprises of organically pertinent entities. These entities such as cells, tissues, and organs are verified and regulated based on different sub-systems in the body they belong to. For instance, biological systems like the digestive system, endocrine system, muscular system, circulatory system, and nervous system just to name but a couple [1,2]. Of all the previously mentioned biological systems, the nervous system is an imperative structure due to its regulation of activities and as well as transmission of signs around the human body.

The nervous system is an extremely intricate component of the human body that controls activities and sensitive information by conveying signals to and from various components of the human body. Specifically, in vertebrates, there exist two subsystems which constitute the nervous system; to be precise they are the central nervous system (CNS) and the peripheral nervous system (PNS) [3]. The PNS encompasses principally of nerves, which are covered packages of long strands or axons that attach the CNS to all other components of the body; while the CNS consists of the brain and spinal cord. Of the aforesaid CNS organs, the brain is quite vital due to its involvement in series of actions as regards information that it receives from the senses and body, and hence sends directives in form of messages back to the body to undertake certain activities.

The human brain is the focal point organ of the human nervous system which works in synergy with the spinal cord, with both being the major constituents of the CNS which comprises of the cerebrum, the brainstem, and the cerebellum. The major functionalities of this organ are coordination of the majority of the tasks of the body, dealing, incorporating, and harmonizing the information it obtains from the sensory organs and thus formulates verdicts which are sent as commands to the rest of the body to perform certain objectives such as instructing the heart to breathe, lungs to inhale and exhale, controlling of body movement; senses and memories just to name a few. Furthermore, the brain is enclosed and shielded by bones of the head called the skull [4].

Owing to the sensitive nature of the brain, it is susceptible to anomalies that can obstruct its smooth functionality in the mode of infections and disorders like Parkinson's disease, Dementia as well as Alzheimer's disease, Stroke, Mental Disorders, and Seizure Disorders just to name but a couple. Of the aforesaid diseases, seizure disorders are the most intimidating of all.

A seizure is a solitary incidence of uncontrolled simultaneous neuronal action in the brain which sometimes lasts within a limited period. However, this unusual unwarranted activity can bring about various indications and side effects such as spasms, thought disturbances, loss of consciousness just to mention but a few. What is more, medical experts view seizures as a consequence of a disease or seizure disorders.

Seizure disorder is a health condition identified with a distinctive feature which is a scenario of unrestrained electrical activity in the brain and consequently fabricates side-effects that involve several seizures, with the resultant effects being a certain level of short-term brain dysfunction [5]. Seizures are intrinsically intertwined to the types of seizure disorders namely non-epileptic and epileptic seizures. Of the abovementioned kind of seizures, the epileptic seizure is the most terrifying of all since they cannot be equivocally controlled.

An epileptic seizure otherwise called epilepsy is a severe non-transmittable seizure disorder of the brain that can be activated with no obvious cause of trigger which tends to happen two or more countless times. Besides, medical professionals cannot specify the actual cause of an epileptic seizure which is most times not known, a situation called idiopathic epilepsy that accounts for half of the epileptic seizure cases worldwide, but relatively it tends to commence after an ill-health, harm to the brain, and encounter with disease-causing mechanisms. However, causes of epilepsy are sub-divided into the following classes such as structural, genetic, infectious, metabolic, immune, and unknown just to name a few [6]. Be that as it may, epileptic seizures may be due to several brain disorders like structural anomalies, strokes, or tumors just to mention but a couple; in situations as this, it is known as symptomatic epilepsy. However, the aforementioned category of epilepsy is quite predominant amongst individuals ranging from newborns to older people.

The symptoms of this disease are loss of consciousness, uncontrollable jerking movements of the arms and legs, sensation (including vision, hearing, and taste), mood (temporary confusion), cognitive functions, and psychic symptoms such as fear, anxiety just name but a few.

The abovementioned symptoms vary depending on the type of seizure affecting the individual. More so, the most familiar type of seizure is convulsive which is accountable for 60% of epileptic seizure cases worldwide, while the other 40% seizure cases are non-convulsive and are characterized by the absence of seizures [7].

According to the World Health Organization, there exist more than 50 million individuals worldwide living with epilepsy; hence, making epilepsy a major and most universal neurological disease globally. Besides, 80% of these individuals with epilepsy live low and middle-income countries of Sub-Sahara Africa and the rest of the world [8].

Besides, three-quarters of persons with epilepsy living in low-income countries do not access to adequate medical treatment for this ailment. Nonetheless, the threat of untimely passing in patients due to epilepsy is three times greater than the death rate of the world's populace. In several parts of the world, due to the convulsive nature of epilepsy, individuals with the ailment and their families are susceptible to stigmatization and discrimination [9]. However, it is of essence that roughly 70% of persons living with epilepsy have a chance of life without a seizure, if and only if the ailment is diagnosed early and treated.

Owing to the convulsive nature of epilepsy, several clinical methods have been utilized in diagnosing epilepsy such as computed axial tomography scan (CT scan), single photon emission computed tomography (SPECT),positron emission tomography (PET), magnetic resonance imaging (MRI),magneto encephalography (MEG), and electroencephalogram (EEG) respectively.

On the other hand, usage of the aforementioned diagnostic methods has the following accompanying inadequacies such as: the use of CT scans on the brain impinges on the bones in close proximity and also exposes patients to high radiation which has the following consequences such as vomiting, bleeding, fainting; SPECT scan test results are difficult to interpret due to lengthy scan times, it has low resolution images despite its scanner being quite expensive making it less available for the financially challenged persons; PET Scanner is very costly with the radioactive elements utilized during scan causing complications to pregnant patients, and also due to the exposure to radioactive rays during testing, there is limitation to the number times a patient can undergo the tests; MRI scans are not appropriate for claustrophobic patients due to time utilized in the enclosed machine, MEG tests cannot determine exactly where in the brain activities are taking place with the signal of interests exceeding a minute; while in EEG testing, it is thorny to detect the exact spot in the brain the electrical activity is emanating from.

Hence, a lot of false-positives are produced as a result of usage of the above-listed methods due to the overlapping symptoms epilepsy has with other seizure disorders leading to misdiagnosis of the aforementioned disease, with several of the abovementioned diagnostic methods quite invasive, dangerous, and capital-intensive. Thus, there is a need to proffer a solution to assist in diagnosing epilepsy. For this reason, the use of artificial intelligence (AI) is seen as a non-invasive and less expensive method that will assist in curbing the menace of misdiagnosis of epilepsy.

What is more, with the tremendous success achieved in the field of artificial intelligence, several machine learning techniques have been utilized in diagnosing epilepsy in the works of [10,11,12,13,14,15,16,17,18,19, 20 and 21] but they generated a lot of false-negative during testing.

In this paper, we expect to apply a supervised AI technique called Bayesian Belief Network (BBN) to diagnose epilepsy. 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 a probability that

connotes the amount where one variable is plausible to impact another. Conversely, BBN was our method of choice on account of its ability to make a prescient inference. The chosen approach uses Bayes theorem which is a statistical technique that guides high accuracy in terms of predicting, detecting events, and its occurrences.

One significant feature the proposed solution has over existing solutions is its capability to diagnose epilepsy just as the overlapping symptoms epilepsy has with other seizure disorders which will bring forth improvement in the following areas: the anticipation of epilepsy, recognition of epilepsy, and diagnosis of seizure disorders with concluding outcomes identified with epilepsy.

However, the paper is organized as follows: Section II contains the related works on epilepsy diagnosis using AI; Section III explains the chosen non-invasive AI method utilized in diagnosing epilepsy, the simulation carried out, results acquired and discussion of obtained results; and Section IV concludes research work with future directions.

2. Related Works

Several studies have been conducted on diagnosing epilepsy using Artificial Intelligence (AI). In [10], a specialized expert system to diagnose epilepsy which relied on expert knowledge was developed. The system detected epilepsy with high detection accuracy. Nevertheless, the expert system had the following inadequacies such as the high cost of implementation and maintenance of the system. Also, there is a level of complicatedness in developing inference rules which may result in providing the wrong diagnosis of diseases. The expert system failed to detect seizure disorders with overlapping symptoms as epilepsy.

In [11], Neural Network (NN) and Fuzzy Logic (FL) were utilized to develop an adaptive neural fuzzy network (ANFN) to detect epileptic seizures. The system detected epileptic seizures with 85.9% detection precision. Besides, the system had the following drawbacks like the complexity to understand the results attained from the learning process of the adaptive neural fuzzy network, the learning process is prolonged and the system adaptive neural fuzzy network end-results cannot be established to determine the trustworthiness due to its black-box nature. Also, the system failed to identify seizure disorders with overlapping symptoms as epilepsy.

In [12], a hybrid expert system for detecting epileptic seizures based on the merger of artificial neural network (ANN) and fuzzy logic (FL) called Adaptive Neuro-Fuzzy Inference System (ANFIS) was developed. The system detected epileptic seizures with an overall detection exactness of 94%. Be that as it may, the system had the following shortfalls such as the inability to identify seizure disorders with overlapping symptoms as epilepsy, the intricacy to comprehend the results obtained from the learning process of the neural network; the learning process is time-consuming, and the system neural network's result cannot be established to see if it is credible owing to its black-box nature.

In [13], Artificial Neural Network (ANN) and Fuzzy Logic (FL) were employed in the development of a dedicated system to diagnose epileptic seizures. The system diagnosed epileptic seizures with 90.16% detection exactness. Nonetheless, the system had the following quagmires such as the difficulty to understand the results acquired from the learning process of the neural network, the learning process taking longer period, and the credibility of the system neural network's outcome cannot be ascertained owing to the black-box nature of neural networks. Also, the system neglected to recognize seizure disorders with overlapping symptoms as epilepsy.

In [14], Fuzzy Adaptive Resonance Theory (ARTMAP) Neural Network was employed in the development of a specialized expert system for detecting epileptic seizures. The system classified epileptic seizures with 93.7% detection precision. Nevertheless, the system had the following accompanying downsides such as the inability to detect seizure disorders with overlapping symptoms as epilepsy, Fuzzy ART networks are not consistent because they rely on the order of training data and sometimes the learning rate; solutions obtained from the learning process of neural networks are difficult to understand, the learning process is prolonged, and the system neural network outcome cannot be established to see if it is convincing owing to its black-box nature.

In [15], Fuzzy Logic (FL) as an approach was employed in the development of a dedicated expert system for detecting epileptic seizures. The fuzzy system identified epileptic seizures with 95.8% detection accuracy. Conversely, the system had the following accompanying shortfalls such as failure to recognize seizure disorders with overlapping symptoms as epilepsy, fuzzy systems don't have the proficiency of machine learning and neural network type pattern recognition; fuzzy systems have the issue of real-time responsiveness and difficulty in making bi-directional inferences. Be that as it may, fuzzy systems are also lacking in tackling uncertainties owing to unawareness, incompleteness, and randomness.

In [16], Fuzzy C-Means was utilized to develop an intelligent expert system to detect electroencephalogram signals during epileptic seizures. The expert system identified epileptic seizures with high detection exactness. Moreover, the system had the following accompanying dilemmas such as Fuzzy C-Means' inability to handle high datasets; then again, it is susceptible to initialization and with ease gets trapped in the local optima. Also, the system failed to detect seizure disorders with overlapping symptoms as epilepsy.

In [17], Artificial Neural Network (ANN) and Particle Swarm Optimization (PSO) algorithm were employed in the development of a dedicated expert system for diagnosing epilepsy. The system diagnosed epilepsy with high detection exactness. Be that as it may, the system had the following accompanying problems such as the complicatedness to identify with the results obtained from the learning process of the neural network, the learning process is time-consuming, and the system neural network outcome' credibility cannot be ascertained to its due to the black-box nature of neural networks. PSO algorithm easily gets trapped in the local optima, it has a low convergence rate in the iteration process, and it is quite complicated to classify initial design parameters. Also, the system neglected to detect seizure disorders with overlapping symptoms as epilepsy.

In [18], Scalar Vector Machine (SVM) was utilized to develop a proficient expert system for automatic detection of epileptic seizures. The specialized expert system classified epileptic seizures with 99.53% detection precision, sensitivity, and specificity rates over 98.8 %. Conversely, the expert system had the following accompanying issues such as the inability to detect seizure disorders with overlapping symptoms as epilepsy; SVM algorithm is deficient in the handling of large datasets, it underperforms in scenarios the dataset has more noise specifically target classes having overlapping features.

In [19], a deep learning technique called convolutional neural network (CNN) was employed in the development of a specialized automated expert system for detecting epilepsy based on encephalography (EEG) signals. The expert system detected epilepsy with a 99.1% detection accuracy based on test data. Be that as it may, the system had the following accompanying downsides such as the intricacy to recognize seizure disorders with overlapping symptoms as epilepsy, CNN is extremely luxurious to train, requires large data to perform very well, it is time-consuming, and make use of a lot of memory to execute the network.

In [20], Fuzzy Logic (FL) and Scalar Vector Machine (SVM) were utilized to develop a dedicated expert system for detecting epileptic seizures based on selected features. The system detected epileptic seizures with 95% detection exactness. What is more, the system had the following accompanying worries such as complicatedness in responding in real-time and making bi-directional inferences, failure to distinguish seizure disorders with overlapping symptoms as epilepsy; fuzzy systems don't have the potentials of machine learning and neural network type pattern recognition. Also, the SVM algorithm is quite deficient in handling large datasets; it does not perform well in situations where the dataset has more noise exclusively target classes with overlapping features.

In [21], An Adaptive Neuro-Fuzzy Inference System (ANFIS) was developed for predicting epilepsy based on the electroencephalogram signals. The system detected epilepsy with a 98.4% detection accuracy. Nonetheless, the system had the following drawbacks such as the intricacy in understanding the solution obtained from the learning process of the neural network; the learning process is time-intensive, and the system neural network outcome cannot be verified to see if it is credible because of its black-box nature. Also, the system failed to detect seizure disorders with overlapping symptoms as epilepsy.

3. Methodology, Simulation, Result and Discussion

3.1 Methodology

In this paper, the technique we intend to employ in diagnosing epilepsy, seizures disorders as well as the overlapping symptoms they share in common is a non-invasive AI method called Machine Learning.

Machine Learning is an alliance of strategies for building models that illustrate or foretell utilizing data or experience. Even so, there are a few techniques of Machine Learning namely Supervised Learning: it trains data and integrates required results (for instance, Bayesian Belief Networks, Neural Networks, Deep Learning and so on.), Unsupervised Learning: it trains data and does leave out wanted results (for example Grouping, Dimensionality Reduction), Semi-Supervised Learning: it trains data and hardly slots in any ideal outcome, and Reinforcement Learning: it gains from series of activities (Temporal Difference Learning, Q-learning) [22].

In this study, we expect to utilize a managed AI method called Bayesian Belief Network because of its prediction ability dependent on experience and example data available to it during training and testing of observed datasets. Bayesian Belief Network (BBN) is a directed acyclic graphical model that utilizes probability to show conditional dependencies that prevails among nodes on a graph [23]. It is a complex probabilistic system that combines expert data and investigative datasets. It designs out the course of circumstances, logical results, and connections between factors; in addition, encodes them with a probability that signifies the amount wherein one variable is likely to influence another. Furthermore, Bayesian Belief Network strives on the Bayes theorem which relies on probability.

The Bayes theorem is represented in the mathematical equation below:

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

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 regularly spoken to as a sort of directed acyclic graph (DAG). A DAG is constituted by the pair (V, E) where: "V" represents nodes (random variables) in the DAG, and "E" symbolizes a collection of directed arcs (arrows) or edges linking vertices together in the DAG.

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

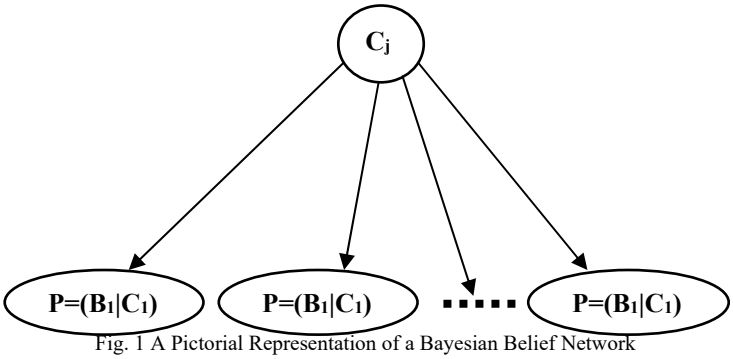

Fig. 1 A Pictorial Representation of a Bayesian Belief Network

A couple of advantages of this model are: it is exceptionally swift in making inferences, the subsequent probabilities are very simple to decipher, the learning algorithm is clear and the model adequately merges with utility functions to make ideal surmisings. In this paper, we expect to recognize epilepsy, seizure disorders, and their symptoms utilizing a managed AI procedure called Bayesian Belief Network (BBN). A model comprising of 61 nodes where a few nodes speak to a type of ailment or element that impact the diagnosis of epilepsy, seizure disorders, and their side effects will be designed utilizing Bayes-Server. An epilepsy dataset will be utilized to train and test the system. Utilizing the Pareto Principle, 80% of the dataset will be utilized to prepare the model while the remainder will be utilized in testing the model. The goal of the model is to accomplish high recognition precision with the employment of the covering indications of seizure disorders and epilepsy.

3.2 Simulation, Results and Discussion

The simulation was performed utilizing an epilepsy dataset in training, testing, and predicting epilepsy which was retrieved from [24]. What is more, previews of the used dataset, designed BBN model for predicting epilepsy, seizure disorders and their manifestations, BBN model convergence chart, log-likelihood batch query chart, feature importance of nodes chart, in-sample anomaly detection chart, likelihood plots of ailments being the cause of seizures disorders and epilepsy, log-likelihood graph for detecting epilepsy and likelihood against log-likelihood plot for predicting epilepsy, seizure disorders and symptoms were taken during the simulation process and appear beneath in figures 2,3,4,5,6,7,8,9,10,11 and 12 respectively with the results discussed underneath the diagrams. On the other hand, the used dataset includes a merge of ailments and factors taken into consideration in the recognition of epilepsy, seizure disorders, and their symptoms signifying 61 with each illness and factor having a value which speaks to the probability of such ailment and factor causing epilepsy and seizure disorders. The ailments and factors are: Absence Seizures, Anxiety, Arms Jerking, Atonic Seizures, Benign Rolandic Epilepsy, Bowel Movement, Bruises, Catamental Epilepsy, Children, Clonic Seizures, Cognitive Functions, Complex Focal Seizures, Convulsions, Dazed, Depression, Drooling, Epilepsy, Epilepsy Categories, Eyes Rolling, Eyes Twitching, Fear, Febrile Seizures, Focal Seizures, Fractures, Frequent Falling To Ground, Generalized Seizures, Genetic, Grand Mal Seizures, Head Dropping, Hearing, Infectious, Immune, Legs Jerking, Lips Jerking, Loss of Consciousness, Menstrual Cycle in Females, Metabolic, Mood, Motor Seizures, Myoclonic Seizures, Non-Motor Seizures, Physical Problems, Psychic Symptoms, Secondary Generalized Seizures, Seizure Disorders, Sensation, Simple Focal Seizures, Simple Partial Seizures, Structural, Sudden Loss of Muscle Tone, Taste, Temporary Confusion, Thought Disturbances, Tongue Biting, Tonic Seizures, Uncontrollable Jerking Movements, Unclassified Seizures, Unknown, Unknown Onset Seizures, Vision, and 6 months to 5years.

Figure 2 below shows a snapshot of the dataset utilized in training, testing, and predicting epilepsy and seizure disorders.

Convulsions	Dazed	Depression	Drooling	Epilepsy	Epilepsy Categories	Eyes Rolling	Eyes Twitching	Fear
-0.844	1.29	0.182	-1.17	-2.24	-0.0383	-0.14	0.173	-0.842
0.495	-0.0955	0.697	0.646	0.478	0.0489	-0.13	-0.737	0.0747
0.929	1.25	0.614	1.37	2.03	-0.808	2.01	0.914	0.921
1.5	-0.0638	-0.991	-0.707	-0.916	1.08	-1.16	-1.51	-0.91
0.804	-0.169	0.912	0.397	-0.79	1.54	2.05	-0.287	0.0562
-1.08	0.895	1.37	-1.24	-0.41	1.38	0.899	-1.55	1.75
-0.119	-1.77	0.327	0.199	-1.05	-2.17	-0.612	0.585	-0.709
-1.49	-2.06	1.35	0.958	-0.11	0.25	-0.532	0.0623	1.55
-0.24	1.41	-1.37	-2	0.2	-0.931	0.65	1.63	1.27
0.255	0.563	0.218	1.25	2.52	0.391	0.971	0.467	0.454
0.689	-0.172	0.0656	-1.69	2.14	-0.563	-0.265	-0.797	0.238
-1.55	-1.36	0.909	0.142	0.0938	-1.9	0.368	0.0257	-0.196
0.406	1.44	1.1	-0.0237	-0.0462	-0.986	-0.335	0.936	0.842
0.636	-1.25	-0.174	0.0431	-0.0698	-1.01	-1.03	0.802	0.811
0.421	-0.167	1.23	0.18	0.903	-0.513	-0.114	0.584	1.08
-1.39	-0.621	0.0184	-0.338	0.906	0.625	-0.761	1.26	0.167
-1.91	-0.0838	0.115	-0.675	-1.25	0.758	0.76	0.139	-0.575
0.022	0.472	-0.843	1.3	-0.358	-0.118	-0.287	-0.072	0.0705
0.671	-0.904	-0.365	-0.121	-0.405	-0.754	0.637	-0.351	-0.0152
1.01	-0.809	0.37	-0.331	0.384	1.31	-0.868	-0.622	-1.66
-0.63	-0.416	-1.64	0.149	-0.45	1.11	2.34	-1.4	0.126
1.3	1.17	0.352	1.59	-1.03	-0.22	0.48	-0.647	-0.65
-0.901	0.903	-1.28	-0.21	1.14	-0.821	1.91	-0.87	-0.286
-0.373	-0.599	-0.748	0.481	-0.406	-1.14	0.0738	0.904	-0.00396

Fig. 2 Snapshot of Dataset

The Bayesian Belief Network model was developed utilizing the Bayes-Server platform. The Bayesian Belief Network (BBN) for predicting epilepsy was structured with the objective that the nodes on the network are linked based on the likelihood of an ailment causing another sickness and factor affecting another factor. In our model, for a case to be classified as epilepsy, the sicknesses and different components that are taken into consideration in the diagnosis of epilepsy are: Anxiety, Arms Jerking, Atonic Seizures, Benign Rolandic Epilepsy, Bowel Movement, Bruises, Catamental Epilepsy, Cognitive Functions, Convulsions, Dazed, Depression, Drooling, Epilepsy Categories, Eyes Rolling, Eyes Twitching, Fear, Fractures, Frequent Falling To Ground, Generalized Seizures, Head Dropping, Hearing, Legs Jerking, Lips Jerking, Loss of Consciousness, Physical Problems, Psychic Symptoms, Seizure Disorders, Sensation, Sudden Loss of Muscle Tone, Taste, Temporary Confusion, Thought Disturbances, Tongue Biting, Uncontrollable Jerking Movements, Unclassified Seizures, and Unknown Onset Seizures respectively.

Figure 3 shows the BBN model for detecting epilepsy, seizure disorders, and their symptoms.

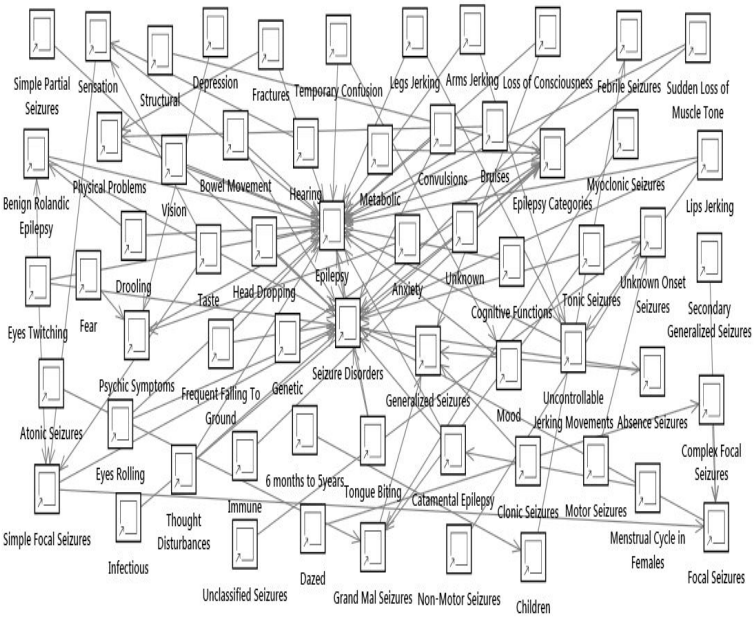

Fig. 3 Bayesian Belief Network Model for Detecting Epilepsy, Seizure Disorders, and Their Symptoms.

Hence, to mathematically represent our model we have:

Epilepsy

$$\%_{i=1}^{61} P(Disease_j) \mid Parents_j(Disease_j) \quad (2)$$

Where,

Disease: Node with a Disease Ailment

Parents ($Disease_i$) = Nodes that converge on Disease $Ailment_{i..}$

The epilepsy dataset in figure 2 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 epilepsy, seizure disorders, and their symptoms at iteration count 2.

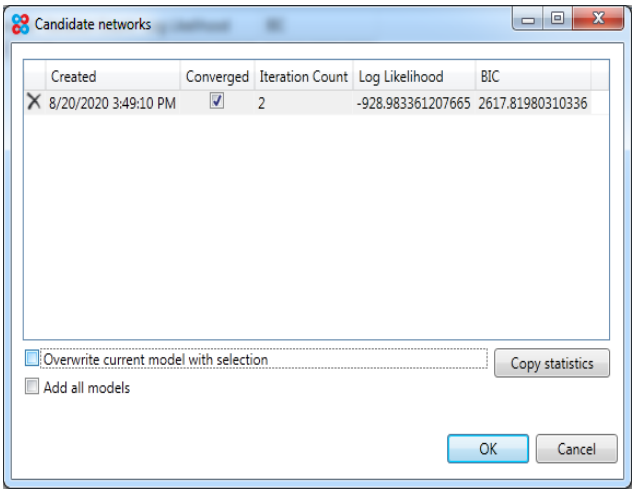

Fig. 4 Bayesian Belief Network Model for Detecting Epilepsy, Seizure Disorders, and Their Symptoms Converging at Time Series 2.

Figures 5,6,7,8,9,10,11 and 12 shows log-likelihood batch query chart for predicting epilepsy, seizure disorders, and their symptoms, feature importance chart of nodes in the BBN model, the in-sample anomaly detection chart, the likelihood plot of seizure types and symptoms prompting a seizure disorder case next to its probabilities; the likelihood plot of epilepsy categories, and their indications prompting an epilepsy infection case alongside its probabilities, the log-likelihood graph for detecting epilepsy, seizure disorders, and their side-effects, and likelihood against log-likelihood for predicting epilepsy, seizure disorders, and their manifestations respectively. The results generated from the simulation demonstrated that the system had the option to anticipate 99% epilepsy, seizure disorders, and their symptoms on the dataset specifically and it had a log-likelihood of 69.5 on the test dataset.

Figure 5 below shows the log-likelihood batch query chart for predicting epilepsy, seizure disorders with their symptoms.

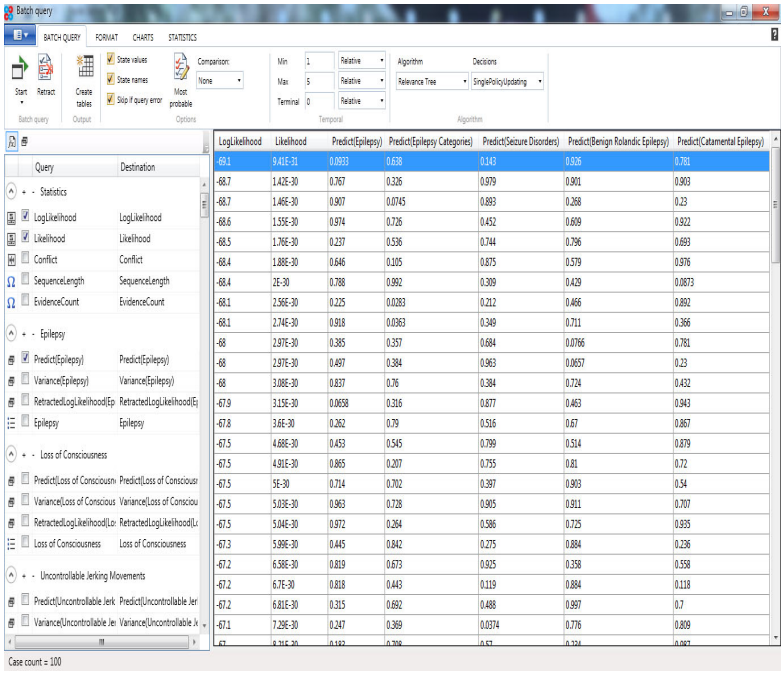

Fig. 5 The Log-likelihood Batch Query Chart for Predicting Epilepsy and Seizure Disorders with their Symptoms.

This log-likelihood batch query chart shows the results of test data employment. Here, 100 experimental cases were conducted and the result acquired from the test data showed the system was able to predict the likelihood of each case of epilepsy, seizure disorders, and their side-effects together with the log-likelihood and likelihood (probability values within 0 to 1) attained from each of the 100 investigational cases and recorded below as follows:

In Experiment 1: The probability of Predict(Epilepsy) was 0.0933, Predict(Epilepsy Categories) was 0.638, Predict(Seizure Disorders) was 0.143, Predict(Benign Rolandic Epilepsy) was 0.926, and Predict(Catamental Epilepsy) was 0.781 in experiment 1 put alongside to 0.0932701374,0.63800131,0.142803500,0.926013003 and 0.780600542 respectively in the test data. Also, Experiment 1 had 9.33%, 63.8%, 14.3%, 92.6%, and 78.1% sensitivity of Epilepsy, Epilepsy Categories, Seizure Disorders, Benign Rolandic Epilepsy, Catamental Epilepsy, and their symptoms after due conclusion of Experiment 1 correspondingly.

In Experiment 2: The probability of Predict(Epilepsy) was 0.767, Predict(Epilepsy Categories) was 0.326, Predict(Seizure Disorders) was 0.979, Predict(Benign Rolandic Epilepsy) was 0.901, and Predict(Catamental Epilepsy) was 0.903 in experiment 2 put next to 0.767001421,0.326014200,0.979011822,0.9006155000 and 0.9027000231 respectively in the test data. What is more, Experiment 2 had 76.7%, 32.6%, 97.9%, 90.1%, and 90.3% sensitivity of Epilepsy, Epilepsy Categories, Seizure Disorders, Benign Rolandic Epilepsy, Catamental

Epilepsy, and their symptoms after completion of Experiment 2 respectively.
In Experiment 3: The probability of Predict(Epilepsy) was 0.907, Predict(Epilepsy Categories) was 0.0745 Predict(Seizure Disorders) was 0.893, Predict(Benign Rolandic Epilepsy) was 0.268, and Predict(Catamental Epilepsy) was 0.23 in experiment 3 judged against 0.907001103,0.074900032,0.892701114,0.268011444 and 0.230000111 respectively in the test data. Besides, Experiment 3 had 90.7%, 7.45%, 89.3%, 26.8%, and 23% sensitivity of Epilepsy, Epilepsy Categories, Seizure Disorders, Benign Rolandic Epilepsy, Catamental Epilepsy, and their symptoms after the due conclusion of Experiment 3 in that order.
Above and Beyond, this experiment continued up to experiment number 100. Hence, the system results showed a 0.0001 value difference between the prediction results and original test data of 100% resulting in 99% prediction accuracy.
Figure 6 shows the feature importance of the linked nodes in the designed BBN model for predicting seizure disorders and symptoms in figure 3 above.

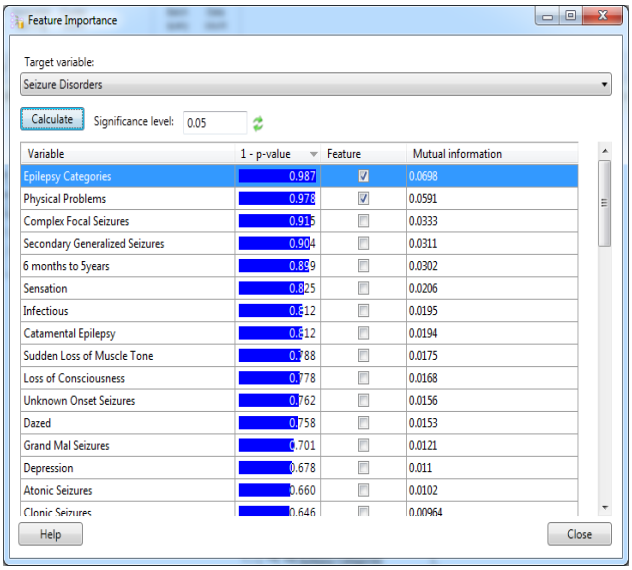

Fig. 6 The Feature Importance Chart for Seizure Disorders Node in the Developed BBN Model

The Feature Importance Chart shows the probabilistic-value (p-value) of the variable (nodes), Feature, and Mutual Information concerning the Seizure Disorders node.
The p-value specifies the likelihood (probability) of the nodes prompting Seizure Disorders.
The Feature box is enabled if that particular node is solely involved, and assists in the detection of Seizure Disorders.
The Mutual Information illustrates the attachment with nodes directly related (i.e. in this case the direct association of the nodes with the Seizure Disorders node) and assigned a value.
The Significance Level signifies the boundary of error encountered in the detection of Seizure Disorders.
Figure 7 shows the feature importance of the allied nodes in the designed BBN model for predicting epilepsy, and its symptoms in figure 3.

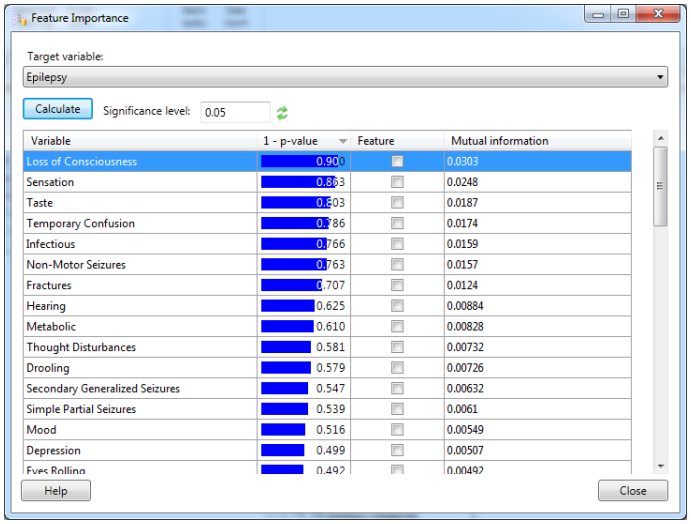

Fig. 7 The Feature Importance Chart for Epilepsy Node in the Designed BBN Model

The Feature Importance Chart shows the probabilistic-value (p-value) of the variable (nodes), Feature, and Mutual information concerning the Epilepsy node.
The p-value specifies the likelihood (probability) of the nodes prompting an Epilepsy infection.
The Feature box is enabled if that precise node is actively involved, and aids the detection of Epilepsy.
The Mutual Information shows the connection with nodes directly linked (i.e. in this case the direct relationship of the nodes with the Epilepsy node) and allotted a value.
The Significance Level point to the margin of error encountered during detection of Epilepsy.
Figure 8 shows the in-sample anomaly detection chart of the developed BBN model in figure 3.

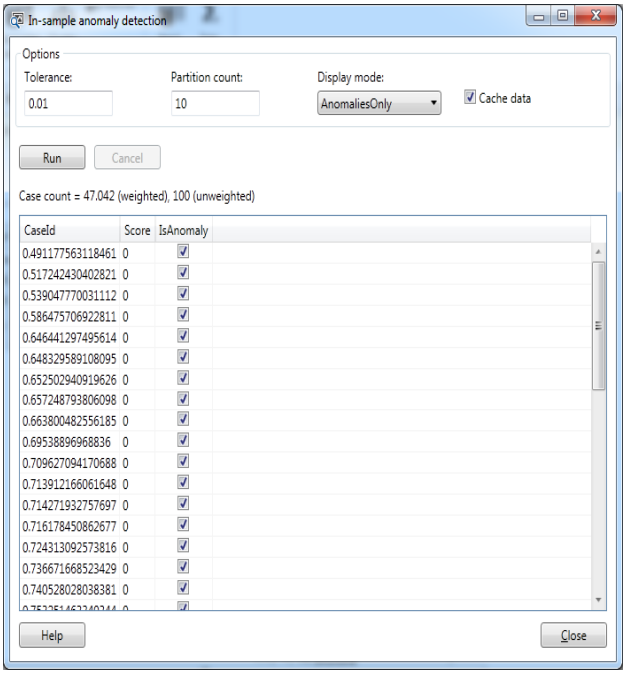

Fig. 8 The In-sample Anomaly Detection Chart of BBN Model

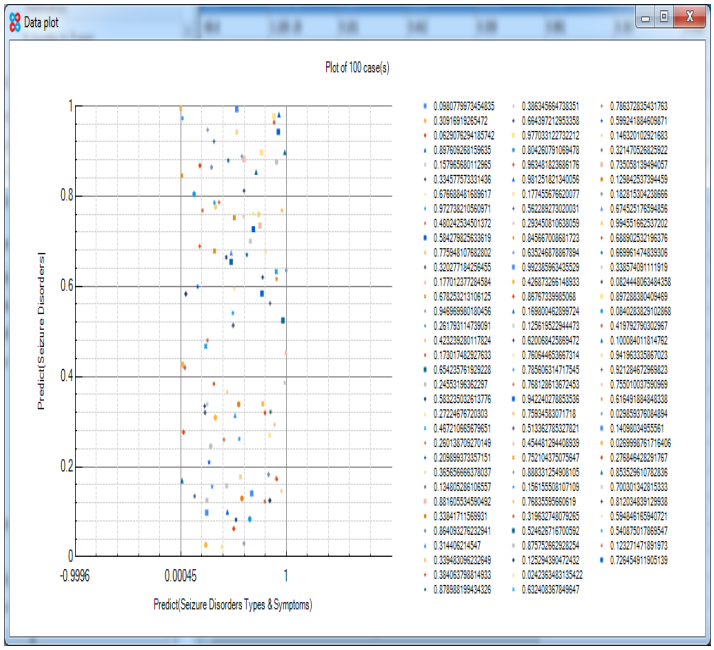

Fig. 9 The Likelihood Plot of Seizure Disorders Types, and Symptoms Prompting a Seizure Disorder Case

The In-sample Anomaly Detection Chart shows 100 experimental tests of recognizing epilepsy and seizure disorders. Each Case is doled out an ID(Identification value) which are estimations of the Predict(Epilepsy), Predict(Epilepsy Categories), Predict(Seizure Disorders), Predict(Benign Rolandic Epilepsy), Predict(Catamental Epilepsy) in figure 5.

The IsAnomaly checkbox is enabled to classify that each case is a confirmed instance of Epilepsy and Seizure Disorders with their side effects. The 100 cases comprises of Epilepsy and Seizure Disorders with their side-effects having a case tally estimation 47.042 (weighted) which entails the impact of the cases prompting Epilepsy and Seizure Disorders. Then again, the 100 (unweighted) implies the number of cases in the pool of information accessible to the system for recognition of Epilepsy and Seizure Disorders and their signs in the dataset pool. The tolerance is the margin of error that could be encountered as regards the detection of the Epilepsy, Seizure Disorders, and their symptoms.

Figure 9 shows the likelihood plot of seizures types and their symptoms of the designed BBN model in figure 3.

Likelihood is used to interpret evidence of unknown parameters. In the dataset, not all values are present; hence the BBN model would have to compute the probability of seizure disorders types, and symptoms prompting a seizure disorder case with some variables missing. Furthermore, the likelihood of an event happening can be graphically represented in a graph called the Likelihood Plot.

A likelihood plot is a graphical method for evaluating if a dataset follows a specified statistical distribution. The likelihood plot above shows the probability of seizure disorders and symptoms prompting a seizure disorder case. In this plot,100 trials were undertaken with each shaded point in the chart named a case and allotted a probabilistic value which is in the scope of 0 to 1 on the Y-axis and 0.0045 to 1 on the X-axis and positioned on the right of the plot. The variable marked “Predict(Seizure Disorders)” is positioned on the Y-axis is plotted against another variable named “Predict(Seizure Disorders Types and Symptoms)” stationed on the X-axis. Nonetheless, from this plot, there are five investigative classes of seizure disorders cases which our system had the option to identify; they are asymptomatic, mild, moderate, severe, and critical classes in the aforesaid order.

Asymptomatic Class: This likelihood class ranges from 0 to 0.2 on Y-axis and 0.0045 to 1 on X-axis. This territory has 22 colored points (cases) which infer 22 cases of no Seizure Disorder ailment whatsoever; thus patients that fall within this class are viewed as being Asymptomatic.

Mild Class: This likelihood class ranges from 0.2 to 0.4 on Y-axis and 0.0045 to 1 on X-axis. This region has 19 tinted points (cases) which correspond to 19 occurrences

of symptomatic patients with Seizure Disorder; and the seriousness level identified as being Mild.

Moderate Class: This likelihood class ranges from 0.4 to 0.6 on Y-axis and 0.0045 to 1 on X-axis. This zone has 13 tinted points (cases) which signify 13 examples of symptomatic patients with Seizure Disorder as well as the significance level classified as being Moderate.

Severe Case: This likelihood class ranges from 0.6 to 0.8 on Y-axis and 0.0045 to 1 on X-axis. This locale has 23 toned points (cases) which symbolize 23 occurrences of symptomatic patients with Seizure Disorder amid the seriousness level recognized as being Severe.

Critical Class: This likelihood class spans from 0.8 to 1 on Y-axis and 0.0045 to 1 on X-axis. This region has 23 toned points (cases) which connote 23 occurrences of symptomatic patients with Seizure Disorder with the severity level identified as being Critical.

All 100 cases in figure 9 had likelihood values less than or equal to 1; with the most essential probability estimation of Seizure Disorder Types and symptoms reported to be 0.994551662537202 which is very well under 1.

Of the 100 experimental cases, the system anticipated 100 cases of Seizure Disorder Types and symptoms prompting Seizure Disorder case extending from asymptomatic, mild, moderate, severe, and critical classes precisely from the test data with 99.45% sensitivity of Seizure Disorder.

Figure 10 shows the likelihood plot of epilepsy categories and indications prompting an epilepsy infection case.

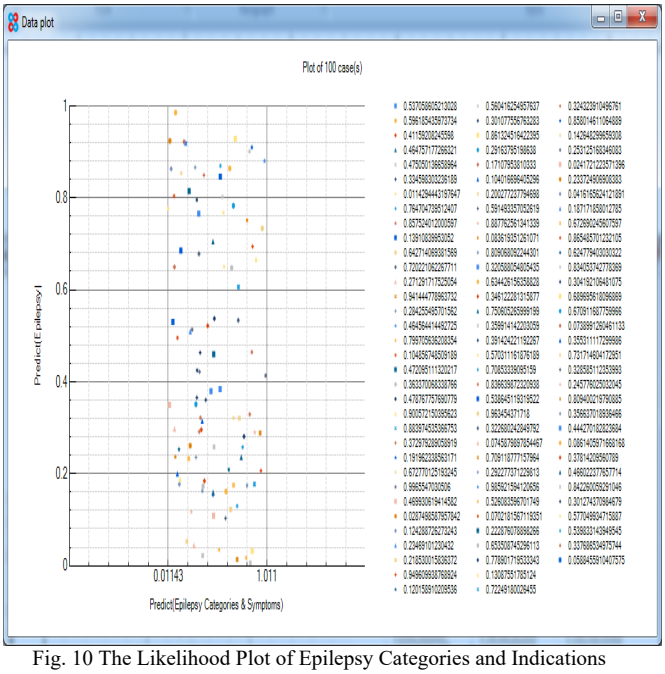

Fig. 10 The Likelihood Plot of Epilepsy Categories and Indications Prompting An Epilepsy Infection Case

The likelihood plot shows the probability of Epilepsy categories and indications prompting an Epilepsy infection case. In this plot,100 experiments were conducted with each colored point in the chart named a case and allotted a probabilistic value which is in the scope of 0 to 1 on the Y-axis and 0.001143 to 1.011 on the X-axis and positioned on the privilege of the plot. The variable marked "Predict(Epilepsy)" is positioned on the Y-axis is plotted against another variable named "Predict(Epilepsy Categories and Symptoms)" situated on the X-axis. Nonetheless, from this plot, there are five diagnostic classes of Epilepsy infection cases that our system had the option to recognize; they are asymptomatic, mild, moderate, severe, and critical classes in the aforementioned order.

Asymptomatic Class: This likelihood class ranges from 0 to 0.2 on Y-axis and 0.001143 to 1.011 on X-axis. This zone has 25 colored points (cases) which infer 25 cases of no Epilepsy infection; thus patients in this class belong to the Immune Epilepsy Category and are viewed as being Asymptomatic.

Mild Class: This likelihood class ranges from 0.2 to 0.4 on Y-axis and 0.001143 to 1.011 on X-axis. This region has 27 tinted points (cases) which match up to 27 occurrences of symptomatic patients with Epilepsy contagion; consequently, patients of this class are members of the Structural Epilepsy Category amid the seriousness level classified as being Mild.

Moderate Class: This likelihood class ranges from 0.4 to 0.6 on Y-axis and 0.001143 to 1.011 on X-axis. This territory has 13 tinted points (cases) which signify 13 examples of symptomatic patients with Epilepsy illness; conversely, patients of this class are affiliates of the Metabolic Epilepsy Category as well as the significance level classified as being Moderate.

Severe Case: This likelihood class ranges from 0.6 to 0.8 on Y-axis and 0.001143 to 1.011 on X-axis. This locale has 17 toned points (cases) which symbolize 17 instances of symptomatic patients with Epilepsy infectivity; on the other hand, patients of this class are classified under the Infectious Epilepsy Category along with the seriousness level recognized as being Severe.

Critical Class: This likelihood class spans from 0.8 to 1 on Y-axis and 0.001143 to 1.011 on X-axis. This region has 18 toned points (cases) which connote 18 occurrences of symptomatic patients with Epilepsy ailment; nevertheless, patients of this class are associates of the Genetic Epilepsy Category with the severity level identified as being Critical.

All 100 cases in figure 10 had likelihood values less than or equal to 1; with the most critical probability estimation of Epilepsy and symptoms reported to be 0.9965547030506 which is very well below 1.

Of the 100 experimental cases, the system anticipated 100 cases of Epilepsy Categories and manifestations prompting an Epilepsy infection case extending from asymptomatic, mild, moderate, severe, and critical classes; Immune, Structural, Metabolic, Infectious and Genetic Epilepsy

Categories precisely from the test data with 99.65% sensitivity of Epilepsy ailment.

Having accomplished the severity levels of epilepsy and seizure disorders ranging from asymptomatic, mild, moderate, severe, and critical classes and epilepsy categories (immune, structural, metabolic, infectious and genetic), we intend to plot the chart for the log-likelihood graph for detecting epilepsy and seizure disorders; likelihood against loglikelihood graph for predicting epilepsy and seizure disorders; in addition, ascertain the log-likelihood value for distinguishing epilepsy and seizure disorders; and, prediction exactness of the BBN model which will be discussed in figure 11 and 12 beneath.

Figure 11 shows the log-likelihood chart for detecting epilepsy and seizure disorders.

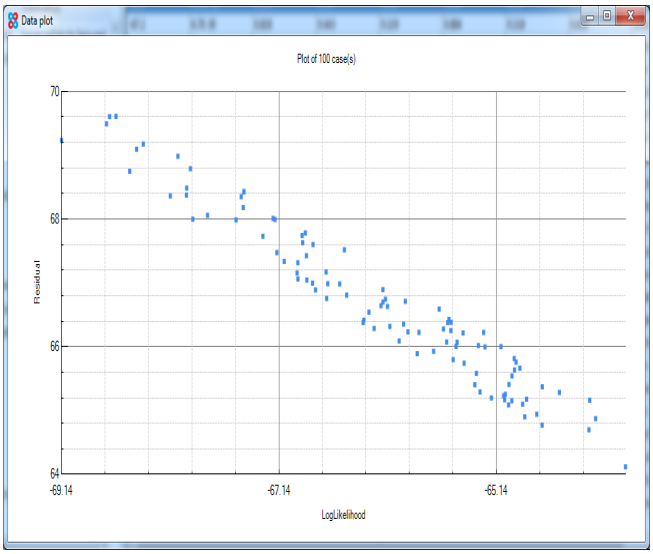

Fig. 11 The Log-likelihood Chart for Detecting Epilepsy and Seizure Disorders

The log-likelihood computes the probability distribution function of all seizure disorders types, and symptoms prompting a seizure disorder case, epilepsy categories and symptoms prompting an epilepsy infection case on the BBN model and sums them up.

Nonetheless, the loglikelihood graph for detecting epilepsy and seizure disorders illustrates residual values on the Y-axis plotted against the loglikelihood values on the X-axis which are independent variables. Even so, a residual value is a scale of how much a regression line vertically fails a data spot. Intrinsically, regression lines are the primary assault of heaps of data. The lines are ordered as averages; on the other hand, a few data spots will match the line and others will miss the spot. In this graph, it shows that 100 experimental cases achieved estimations of 69.5, 69.45,69, 68.99, 69.95, 68.75, 68.50,68.25….and 64.15 respectively. Then again, residual values should be equally and spontaneously isolated around the level lines. Taking a viewpoint on the system' experimental results acquired from the even lines on the outline, it might be seen that where the uppermost residual value and the loglikelihood independent factor accomplished congregates at -68.14 on the horizontal line with 70 being the most vital value that can be reached on the vertical line. The residual value achieved is 69.5 and loglikelihood independent esteem is -68.14.

Thus, the attained log-likelihood value for recognizing epilepsy, seizure disorders, and their side-effects is 69.5.

Figure 12 shows the likelihood against log-likelihood for predicting epilepsy, seizure disorders with their manifestations of the designed BBN model in figure 3.

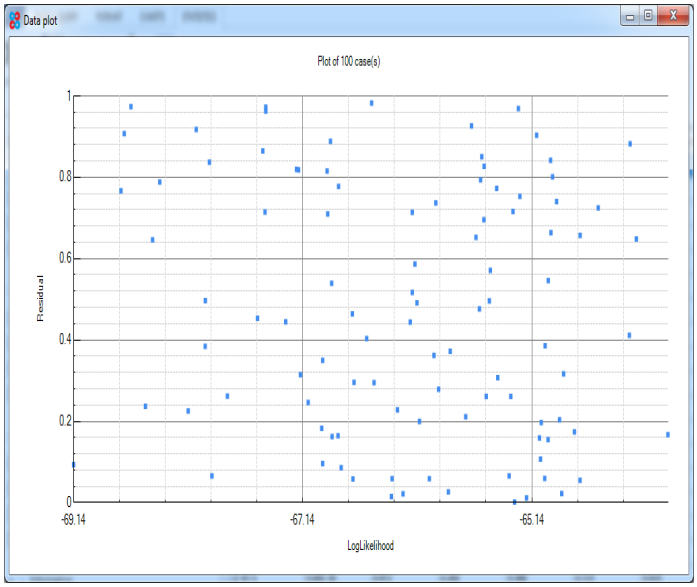

Fig. 12 The Likelihood against the Log-likelihood Graph for Predicting Epilepsy, Seizure Disorders with Their Manifestations.

The likelihood against log-likelihood plot for epilepsy and seizure disorders and their manifestations shows the residual (likelihood) on the Y-axis plotted against the log-likelihood on the X-axis both of which are independent variables. Yet, the likelihood of event (Epilepsy and Seizure Disorders Prediction) occurring are probabilistic values placed between 0 and 1. In this plot, 100 probing cases were conducted which achieved the estimations of 0.9998, 0.9997, 0.9996, 0.9995, 0.9992, 0.9990, 0.8995, 0.8990,…..0.0001,0 individually. Besides, residual (likelihood) values ought to be consistently and haphazardly stretched around the level lines. Viewing the system' tentative results obtained from the level lines on the diagram, it will in general be seen that the residual probability value attained is 0.9998, and the log-likelihood independent value is –66.14.

So, in this system, the most crucial likelihood esteem that can be attained is 1. With 1, being the 100 % residual (probability) rate mark, to get our exactness precision rate, we divide attained likelihood probability esteem by the

highest likelihood value that can be attained and increase by the most imperative residual mark, that is 0.9998/1*100% = 99.98% forecast exactness rate on the test data.

Besides, the likelihood graphs in figure 9, 10 showcased all classes of severity status of seizure disorders types and symptoms prompting seizure disorders, epilepsy categories and symptoms prompting an epilepsy infection case ranging from asymptomatic, mild, moderate, severe, and critical classes as well as the epilepsy categories (immune, structural, metabolic, infectious and genetic) independently with their probabilities while figure 11 demonstrated the system loglikelihood estimation of 69.5 for distinguishing epilepsy, seizure disorders and their manifestations while the likelihood against loglikelihood prediction plot of epilepsy, seizure disorders and their manifestations in figure 12 established a 99.98% prediction precision of the system.

Nonetheless, the likelihood, given evidence of seizure disorder types and symptoms prompting a seizure disorder case is denoted as:

P(Seizure Disorder| Absence Seizures, Anxiety, Arms Jerking, Atonic Seizures, Benign Rolandic Epilepsy, Bowel Movement, Bruises, Catamental Epilepsy, Children, Clonic Seizures, Cognitive Functions, Complex Focal Seizures, Convulsions, Dazed, Depression, Drooling, Epilepsy, Epilepsy Categories, Eyes Rolling, Eyes Twitching, Fear, Febrile Seizures, Focal Seizures, Fractures, Frequent Falling To Ground, Generalized Seizures, Genetic, Grand Mal Seizures, Head Dropping, Hearing, Infectious, Immune, Legs Jerking, Lips Jerking, Loss of Consciousness, Menstrual Cycle in Females, Metabolic, Mood, Motor Seizures, Myoclonic Seizures, Non-Motor Seizures, Physical Problems, Psychic Symptoms, Secondary Generalized Seizures, Seizure Disorders, Sensation, Simple Focal Seizures, Simple Partial Seizures, Structural, Sudden Loss of Muscle Tone, Taste, Temporary Confusion, Thought Disturbances, Tongue Biting, Tonic Seizures, Uncontrollable Jerking Movements, Unclassified Seizures, Unknown, Unknown Onset Seizures, Vision, and 6 months to 5years) = 0.994551662537202.

The likelihood, given evidence of epilepsy categories and manifestations prompting an epilepsy infection case is denoted as:

P(Epilepsy| Anxiety, Arms Jerking, Atonic Seizures, Benign Rolandic Epilepsy, Bowel Movement, Bruises, Catamental Epilepsy, Cognitive Functions, Convulsions, Dazed, Depression, Drooling, Epilepsy Categories, Eyes Rolling, Eyes Twitching, Fear, Fractures, Frequent Falling To Ground, Generalized Seizures, Head Dropping, Hearing, Legs Jerking, Lips Jerking, Loss of Consciousness, Physical Problems, Psychic Symptoms, Seizure Disorders, Sensation, Sudden Loss of Muscle Tone, Taste, Temporary Confusion, Thought Disturbances, Tongue Biting, Uncontrollable Jerking Movements, Unclassified Seizures, and Unknown Onset Seizures) = 0.9965547030506.

From the experiment, it will in general be viewed that our model has a higher residual loglikelihood value which is 69.5; overall, a prediction exactness of 99.98%; 99.65%, and 99.45% sensitivity of epilepsy and seizure disorders in that order.

At long last, comparing the 99.98% prediction exactness of our model with the works conducted by [11,12,14,15, ,18,19, 20 and 21] which has 85.9%, 94%, 90.16%, 93.7%, 95.8%, 99.53%, 99.1%, 95% and 98.4% prediction exactness individually, it is apparent our model has a superior prediction precision than the aforementioned systems. The higher prediction exactness attained by our model could be as a result of the size of the dataset used in training and testing the model in the same way as its capability to anticipate the covering symptoms of epilepsy and seizure disorders, which assisted in the high detection exactness of the abovementioned ailments.

4. Conclusions

Epilepsy is an unceasing brain ailment that is continual and distinguished by impulsive seizures which affect individuals of all ages with the human brain being the spot where it originates from with no evident cause of trigger which has tendencies of causing countless health issues. Seizure practically influences any part of the body; however, the electrical event that fabricates the indications takes place in the brain.

Owing to the spastic nature of epilepsy, in recent past, several systems have been utilized in diagnosing epilepsy and seizure disorders with the sole aim of alleviating the ailment because of it being labeled the most common neurological disease globally; also, owing to late diagnosis and misdiagnosis of the aforesaid disease an area health and information technology experts are making noteworthy attempts to improve.

In this paper, we used an AI method called Bayesian Belief Network to predict epilepsy, seizure disorders, and their manifestations. The model had 61 nodes with each node addressing a select ailment and factors that influence the diagnosis of epilepsy, seizure disorders, and their side-effects. The model was trained and tested and had a general prediction accuracy of 99.98% and a loglikelihood estimation of 69.5 in predicting epilepsy, seizure disorders with their symptoms; 99.65%, and 99.45% sensitivity of epilepsy, seizure disorders in that order. In this paper, we focused on the symptoms of epilepsy, seizure disorders which supported the model' inference mechanism for early diagnosis of the aforementioned ailments.

For future works, there is need to integrate more data inclined by the disease in other to advance the prescient

and obtain optimal outcomes which will be employed and lead to enhancement in the accompanying areas: prediction and detection of epilepsy and seizure disorders.

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