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An Ischemic Heart Disease Prediction Model Based on Observed Symptoms Using Machine Learning

Solomon Osarumwense Alile[1*]

[1*]*Department of Computer Science, Faculty of Physical Sciences, University of Benin, Benin City, Nigeria*

e-mail: *solomon.alile@physci.uniben.edu*

**Corresponding Author: solomonalile007@gmail.com*

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Abstract:- Ischemic Heart Disease is a death-defying cardiovascular disease that disrupts the circulation of blood owing to plaques such as fats, cholesterol, calcium, and other substances resident in the blood, which coagulates hence narrowing the arteries. The symptoms of this disease are angina, sweating, nausea, breathlessness, heart attack, vomiting, pains of back, jaw, shoulder, arm, back, and neck, just to name but a couple. According to World Health Organization, the leading cause of death which has caused over 17 million untimely deaths of patients since 2015 to date especially individuals below the age of 70 years is Ischemic Heart disease which is a form of Cardiovascular Disease; where 81% of these recorded deaths occurring in individuals in respective of sex, particularly in low and middle-income countries of Sub-Sahara Africa. Nevertheless, in the recent past, a couple of systems have been developed to detect this non-transmittable ailment. Yet, they delivered a ton of bogus negative during testing and could not distinguish Ischemic Heart Disease given its covering symptoms it imparts to other Cardiovascular Diseases. Consequently, there was the need to proffer a solution for the issue of under-diagnosis and misdiagnosis of Ischemic Heart Disease, which is much uncontrolled in Sub-Sahara Africa. Hence, in this paper, we proposed and built up a model to predict Ischemic Heart Disease and Cardiovascular diseases using an AI technique called Bayesian Belief Network. The model was structured using Bayes Server and tested with data retrieved from the UCI Machine Learning Repository. The model had an overall prediction exactness of 99.99%; 98.86% and 99.66% sensitivity of Ischemic Heart Disease and Cardiovascular Diseases correspondingly.

Keywords: Ischemic Heart Disease, Cardiovascular Diseases, Detection, Prediction, Machine Learning, Supervised Machine Learning, Bayesian Belief Network

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1. Introduction

The human body is a multifaceted structure made up of cells, tissues, and organs all under the regulatory auspices of biological systems such as digestive system, endocrine system, muscular system, and the circulatory system just to name but a few [1]. Of all the systems above, the circulatory system is an imperative framework due to its control on the circulation of blood around the human body.

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The circulatory system is a biological framework that authorizes circulation of blood and movement of nutrients in the form of amino acids and electrolytes, hormones, carbon dioxide, and oxygen into and out of cells resident in the human body, thus supplying essential nutrients needed to aid combating diseases, normalizing body temperature and pH (potential of Hydrogen), and preserving homeostasis [2]. Furthermore, the circulatory system of humans is usually enclosed, that is the blood running within the system never departs the set-up of blood vessels. However, the system above works in synergy with other biological systems such as the digestive system and lymphatic system, just to mention but a few for optimal functionality of the system and the human body. What is more, this system above also, called the cardiovascular system comprises vital components, namely heart, blood, and blood vessels. Of the abovementioned components of the circulatory system, the heart is the essential organ of this system.

The human heart is the organ liable for the pumping of oxygenated blood to the body and deoxygenated blood to the lungs. It consists of the atrium, ventricle responsible for the circulation of blood, where their circulation procedure is termed systemic and pulmonary. Nevertheless, the previously mentioned constituents of the heart are stationed on the left and right of the heart earning the names left atrium, left ventricle, right atrium, and right ventricle [3]. Despite the functionality of this organ to the smooth running of the circulatory system, it is at risk of infections and diseases which can disrupt the operational functionality it offers to the circulatory system such as congenital heart disease, arrhythmia, dilated cardiomyopathy, myocardial Infarction, heart failure, hypertrophic cardiomyopathy, and ischemic heart disease just to name but a few. Of the previously mentioned diseases, ischemic heart disease is dreaded of all.

Ischemic Heart Disease (IHD) is a non-communicable life-threatening heart disease that entails the diminution of blood circulation to the heart muscle owing to plaques such as fat, cholesterol, calcium, and other substances found in the blood which hardens up, and thus, narrowing the arteries [4]. The symptoms are angina, sweating, nausea, breathlessness, heart attack, vomiting, pains of back, jaw, shoulder, arm, back, and neck, just to mention but a few. Ischemic Heart Disease otherwise called Coronary Artery Disease (CAD) is said to commence with injury to the interior stratum of a coronary artery which might occur early in persons in respective of age and sex. Nonetheless, males are usually at superior risk of Ischemic Heart Disease compared to females whose risk tends to amplify after attaining menopause.

Nevertheless, Ischemic Heart Disease as a form of cardiovascular disease (CVD) is the foremost cause of death worldwide with more patients dying as a result of CVDs than any other confirmed source of death. In 2015, the death toll of patients below the age of 70 years owing to non-transmittable diseases stood at approximately 17 million, of which more than 81% of these confirmed death cases occurred in men and women of low and middle-income countries in Sub-Sahara Africa and rest of the world; with 37% of the passings due to CVDs. Also, heart attacks and stroke accounted for 7.2 million and 5.7 million of the reported deaths in that order. Similarly, a year later, 17.9 million deaths were recorded due to CVDs bringing the percentage of passing globally in that year to over 30%. Also, 85% of these accounted passings were due to stroke and heart attacks. Conversely, going by the latest development of increased recorded deaths all due to CVDs, it is suggested that by the year 2030, approximately 23.6 million passings of patients with CVDs will be recorded majorly from stroke and heart attacks [5]. Be that as it may, Ischemic Heart Disease is not deemed as an infectious ailment rather, it is categorized as a non-transmittable illness that is dynamic (generally deteriorates over time) and an under-analyzed and misdiagnosed death-defying heart ailment that will prompt passing if not diagnosed early and treated.

Due to complications encountered from heart diseases resulting in the passings of patients, several clinical methods have been utilized in diagnosing Ischemic Heart Disease such as Baseline Electrocardiography (ECG), Exercise Radioisotope test Echocardiography (Nuclear Stress Test), Coronary Angiography, Intravascular Ultrasound (IVUS) and Magnetic Resonance Imaging (MRI) just to name a couple. Nonetheless, this usage of the aforementioned diagnostic methods has the following inadequacies such as IVUS testing is time-consuming, MRI scans are not suitable for claustrophobic patients due to time utilized in an enclosed machine, Coronary Angiography tests can only be performed during active bleeding and can cause kidney damage due to the dye utilized during testing, Nuclear Stress Tests causes low blood pressure which might cause patients to faint or feel dizzy, Baseline Electrocardiography tests employs static pictures which might not detect core heart issues in patients with sporadic chest pain due to severe ischemic heart disease. Consequently, utilizing the above-listed diagnostic methods, lot of false-positives were encountered due to the overlapping symptoms ischemic heart disease has with other cardiovascular diseases leading to misdiagnosis of the above 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 Ischemic Heart Disease. Thus, in this paper we intend to utilize a non-invasive method called artificial intelligence (AI) that will assist in curbing the menace of misdiagnosis of Ischemic Heart Disease.

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What is more, with the tremendous success achieved in artificial intelligence, several machine learning techniques has been utilized in diagnosing Ischemic Heart Disease in the works of [6, 7, 8, 9,10,11,12,13,14,15,16,17, 18,19,20,21,22,23,24 and 25], but they generated a lot of false-negatives during testing and were unable to detect Ischemic Heart Disease due to the overlapping symptoms the disease shares with cardiovascular diseases.

In this paper, we expect to apply a supervised AI strategy called Bayesian Belief Network (BBN) to analyze Ischemic Heart 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 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 strategy utilizes Bayes theorem, which is a statistical formula that guides high accuracy in predicting, detecting events, and their occurrences.

One significant feature the proposed solution has over existing solutions is its capability to diagnose Ischemic Heart Disease and cardiovascular diseases just as the overlapping symptoms Ischemic Heart Disease has with other cardiovascular diseases which will bring forth improvement in the following areas the anticipation of Ischemic Heart Disease, recognition of Ischemic Heart Disease and diagnosis of cardiovascular diseases with eventual outcomes identified with Ischemic Heart Disease.

However, the remainder of the paper is arranged as follows: Section II contains the related works on Ischemic Heart Disease diagnosis using AI, Section III explains the chosen methodology utilized in diagnosing Ischemic Heart 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

In recent past, several studies have been carried out on diagnosing Ischemic Heart Disease using Artificial Intelligence. In [6], Fuzzy Cognitive Maps (FCMs) was employed to create a specialized system called Decision Support System for diagnosing Coronary Artery Disease (CAD). The system diagnosed CAD with 78.2% identification precision. However, the expert system had some accompanying dilemmas, such as the inability to detect cardiovascular diseases (CVDs) with overlapping side-effects as Ischemic Heart Disease. Also, FCM algorithm is deficient in handling a large number of variables in the dataset.

In [7], Fuzzy Logic (FL) as an approach was utilized to develop a specialist system to diagnose heart disease. The expert system had 94% identification exactness on test data. What is more, the specialized system had the following accompanying concerns such as difficulty in recognizing cardiovascular diseases (CVDs) with overlapping symptoms as Ischemic Heart Disease. Moreover, fuzzy systems do not have the potentials of machine learning and neural network type pattern identification; also, the fuzzy system had issues of real-time responsiveness and difficulty in making bi-directional inferences.

In [8], The Adaptive Neural Fuzzy Inference System (ANFIS) approach was used to develop a system for diagnosing heart disease. The hybrid system diagnosed heart diseases with high discovery exactness on test data. What is more, the system had the following drawbacks, such as the difficulty in understanding the result acquired from the learning process of the neural network; the learning process is time-consuming, and the system neural network outcome cannot be verified to see if it is credible. Also, the system failed to detect cardiovascular diseases (CVDs) with overlapping symptoms as Ischemic Heart Disease.

In [9], Fuzzy Logic (FL) was employed to design an expert system for diagnosing cardiac diseases. The system detected cardiac diseases with high recognition accuracy. However, the system failed to identify cardiovascular diseases (CVDs) with overlapping symptoms as Ischemic Heart Disease. What is more, fuzzy systems do not have the potentials of machine learning and neural network type pattern identification; also, the fuzzy system had issues of real-time responsiveness and difficulty in making bi-directional inferences.

In [10], Fuzzy Logic was used to develop weighted rules for a clinical decision support system (CDSS) for diagnosing heart diseases. The proposed system analyzed heart disease with high detection accuracy. Nonetheless, the fuzzy system had some accompanying quandaries like the issue of handling real-time sensitivity and intricacy in making bi-directional deduction; fuzzy expert systems do not have the latent of AI techniques such as machine learning and neural network type pattern discovery. Additionally, the fuzzy system failed to recognize cardiovascular diseases (CVDs) with overlapping side-effects as Ischemic Heart Disease.

In [11], Fuzzy Logic was utilized in the development of a dedicated system for detecting heart diseases. The specialized expert system distinguished heart diseases with a general detection precision of 92%. Nevertheless, the system had some accompanying dilemmas

like the powerlessness of classifying cardiovascular diseases (CVDs) with overlapping symptoms as Ischemic Heart Disease. Also, the system failed to handle issues of real-time responsiveness and difficulty in making bi-directional inferences; fuzzy expert systems do not have the potentials of AI techniques such as machine learning and neural network type pattern discovery. Also, justification and authentication of fuzzy systems need extreme testing with hardware.

In [12], Fuzzy C Means (FCM) as an approach was employed in developing a specialized fuzzy expert system with the aim of predicting heart attacks. The system foretells heart attacks with 92% detection exactness. Even so, the system had the following accompanying inadequacies, such as the weakness of identifying cardiovascular diseases (CVDs) with overlapping side-effects as Ischemic Heart Disease. Also, Fuzzy C Means has problems managing high datasets, and it is susceptible to initialization, and without difficulty gets ensnared in the local optima.

In [13], a soft computing technique called Fuzzy Logic was used to develop an expert system for the forecasting of risk levels of heart diseases. The system foretold heart diseases with high detection exactness. However, the system failed to identify cardiovascular diseases (CVDs) with overlapping symptoms as Ischemic Heart Disease. Besides, fuzzy systems do not have the potentials of machine learning and neural network type pattern identification; also, the fuzzy system had corcern of real-time responsiveness; complicatedness in making a bi-directional conclusion.

In [14], Fuzzy Logic (FL) and Decision Trees (DT) were employed to develop a hybrid system to predict coronary heart disease. The system predicted coronary heart disease with 69.51% prediction exactness on test data. However, the system had the following accompanying problems like the intricacy of recognizing cardiovascular diseases (CVDs) with overlapping side-effects as Ischemic Heart Disease. Besides, fuzzy systems do not have the capability of machine learning and neural network type pattern recognition; also, the fuzzy system had issues of handling real-time responsiveness; complicatedness in making a bi-directional deduction. Furthermore, unbalance nature of trees is synonymous with decision trees, quite imprecise, and outcome derived from the decision trees are sometimes partial, which are usually in support of features that have secured more echelon in the created decision tree.

In [15], Fuzzy Logic was used in the development of an expert system for diagnosing heart disease. The system detected heart diseases with 92% detection accuracy. On the other hand, the system had the following accompanying predicaments, such as complicatedness to detect cardiovascular diseases (CVDs) with overlapping symptoms as Ischemic Heart Disease. Additionally, fuzzy systems do not have the prospects of machine learning and neural network type pattern recognition; moreover, fuzzy systems have a concern of real-time reaction and intricacy in making a bi-directional deduction.

In [16], Fuzzy Logic as a soft computing technique was employed in the development of a specified system for classifying coronary artery disease. The expert system had 92.8% identification exactness on test data. All the same, the expert system had the following accompanying concerns such as difficulty in making bi-directional inferences, the disability of fuzzy systems possessing the potentials of machine learning, and neural network type pattern identification; more so, fuzzy systems have the quandary of real-time responsiveness. What is more, the expert system failed to identify cardiovascular diseases (CVDs) with overlapping symptoms as Ischemic Heart Disease.

In [17], Fuzzy logic was utilized in developing a dedicated expert system for diagnosing coronary artery disease. The specialized system had 73.78 forecast exactness, 71.94% sensitivity, and 76.52% specificity on test data. However, the system had the following accompanying inadequacies such as difficulty in recognizing cardiovascular diseases (CVDs) with overlapping symptoms as Ischemic Heart Disease and making bi-directional inferences. Also, fuzzy systems lack the potentials of machine learning, and neural network type pattern recognition, and have the dilemma of real-time sensitivity.

In [18], an ensemble machine learning (Adaptive Boosting algorithm) and prediction models (K-S measures (Kolmogorov-Smirnov), F-score, ROC (Receiver Operating Characteristic) curve were utilized in the development of a hybrid expert system for diagnosing coronary heart disease. The system had 80.14%, 89.12%, 77.78%, and 96.72% identification accuracies on 4 test data. Nonetheless, the hybrid system had the following accompanying dilemmas such as the issue of data imbalance which leads to a decrease in classification accuracy in Adaptive Boosting algorithm, K-S measure can only be utilized for continuous distribution; f-score does not unravel general information among variables in the dataset, ROC Curve calculations are too bulky without dedicated software applications. What is more, the system failed to make bi-directional inferences and detect cardiovascular diseases (CVDs) with overlapping symptoms as Ischemic Heart Disease.

In [19], Fuzzy Logic and Data Mining were utilized in the development of a specialized hybrid system for diagnosing coronary artery disease. The system achieved 81.82% prediction exactness on test data. Nevertheless, the expert system had the following accompanying quagmires such as intricacy in making a bi-directional inference; fuzzy systems do not have the competence of machine learning and neural network type pattern identification; also fuzzy systems

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have issues of handling real-time responsiveness. Besides, the usage of the Data Mining technique violates system user's privacy; it has performance issues as regards results generated using this technique. Also, the hybrid system could not make bi-directional inferences on test data and detect cardiovascular diseases (CVDs) with overlapping side-effects as Ischemic Heart Disease.

In [20], Fuzzy Logic was employed to design system for diagnosing heart diseases. The system attained 93.3% prediction precision on test data. However, the proposed system had the following accompanying quandary, such as the inability to identify cardiovascular diseases (CVDs) with overlapping side-effects as Ischemic Heart Disease. Additionally, fuzzy systems do not have the capability of machine learning and neural network type pattern classification; more so, fuzzy systems have a concern of real-time responsiveness and complication in making bi-directional inferences.

In [21], Fuzzy Logic was utilized in the creation of a dedicated enhanced system for diagnosing coronary artery disease. The proposed system achieved 94.5% prediction exactness on test data. However, the expert system had the following accompanying issues, such as the inability to categorize cardiovascular diseases (CVDs) with overlapping symptoms as Ischemic Heart Disease. Besides, the system could not handle the concern of real-time responsiveness and intricacy in making bi-directional deduction; fuzzy expert systems lack the proficiency of AI techniques such as machine learning and neural network type pattern detection. Also, justification and authentication of fuzzy systems need extreme testing with hardware.

In [22], a machine learning-based technique called Data Mining was employed in the development of a system for diagnosing coronary artery disease. The proposed system attained a high detection precision. What is more, the proposed system had the following accompanying constraints, such as the failure to identify cardiovascular diseases (CVDs) with overlapping side-effects as Ischemic Heart Disease. Moreover, the use of the Data Mining technique defies system user's privacy. Also, it has performance issues concerning outcome produced using this procedure.

In [23], Fuzzy Logic was used to develop a rule-based system for diagnosing coronary heart disease. The proposed expert system attained 72.6% recognition precision on test data. What is more, the proposed system had the following inadequacies, such as intricacy in handling real-time responsiveness and making bi-directional inferences; fuzzy expert systems lack the ability of AI techniques such as machine learning and neural network type pattern identification. Also, justification and authentication of fuzzy systems need intense testing with hardware.

In [24], Dense Neural Network with Hyper Parameter Tuning was utilized in the creation of a dexterous expert system for predicting coronary artery disease. The proposed system achieved a 94.91% prediction precision on test data. Nevertheless, the system had the following accompanying constraints, such as the difficulty of classifying cardiovascular diseases (CVDs) with overlapping manifestations as Ischemic Heart Disease. More so, Neural Networks has less summing up performance concern; it has a worry of arriving at the local minimum and has over-fitting constraints, the neural network convergence speed is generally moderate. The solution attained from the learning process is not easy to decipher. Also, the learning process is time-intensive.

In [25], Convolutional Neural Network (CNN) was employed in the development of a proficient system for predicting coronary heart disease. The proposed system attained 79.5% general prediction exactness on test data. Be that as it may, Neural Networks has a concern of showing up at local minimum and has over-fitting quandaries; it requires many data for learning, computationally expensive, wearisome, and has the black-box nature. It does not offer data about the overall importance of the different limits; it has less summing up performance concern; the neural network convergence speed is moderately moderate. Additionally, the system failed to detect cardiovascular diseases (CVDs) with overlapping manifestations as Ischemic Heart Disease.

3. Methodology

Machine learning is an alliance of strategies for constructing models that delineate or foretell utilizing data or experience. Be that as it may, there are a few sorts of AI namely Supervised Learning: it trains data and incorporates wanted outputs (for example Bayesian Belief Networks, Neural Networks, Deep learning and so on.), Unsupervised Learning: it trains data and does exclude wanted yields (for example Grouping, Dimensionality Reduction), Semi-Supervised Learning: it trains data and incorporates hardly any ideal outcome and Reinforcement Learning: it gains from succession of activities (Temporal Difference Learning, Q-learning) [26]. In this paper, we expect to utilize a managed AI method called Bayesian Belief Network because of its prescient ability dependent on past experience and example data available to its during training and testing of observed datasets.

Bayesian Belief Network (BBN) is a directed acyclic graphical model that utilizes the likelihood to show conditional dependencies that prevails among nodes on a graph [27]. It is a complex probabilistic system that blends expert information and exploratory datasets. It designs out the course of circumstances and logical results connections between factors and encodes them with the probability that

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signifies the amount wherein one variable is plausible to impact another. Furthermore, Bayesian Belief Network strives on the Bayes hypothesis, which relies on probability.
The mathematical representation of the Bayes theorem is shown in the 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 often symbolized as a kind 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 representation of a Bayesian Belief Network.

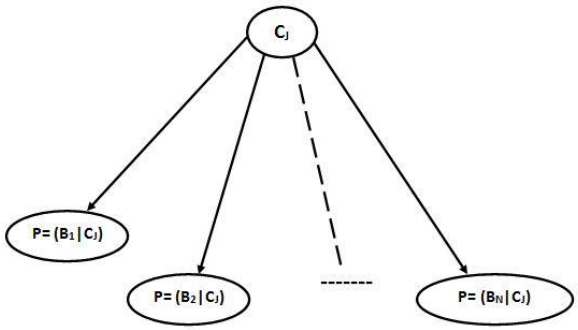

Figure 1: A Pictorial Representation of a Bayesian Belief Network

A few preferences of this model are: it is very speedy in making inferences, the resulting probabilities are quite easy to decipher, the learning algorithm is very straightforward, and the model sufficiently consolidates with utility functions to make optimal inferences. In this paper, we expect to recognize Ischemic Heart Disease, and its symptoms utilizing a managed AI procedure called Bayesian Belief Network (BBN). A model comprising of 92 nodes where a few nodes speak to a type of ailment or factors that impact diagnosis Ischemic Heart Disease, Cardiovascular Diseases (CVDs), and their side-effects will be structured using Bayes Server platform. A Cardiovascular disease dataset will be employed to train and test the system. Be that as it may, using the Pareto Principle; 80% of the dataset will be used to prepare the model while the remainder will be utilized in testing the model. The point of the model is to accomplish high identification exactness with the utilization of the covering indications of Cardiovascular Diseases and Ischemic Heart Disease.

4. Simulation, Results and Discussion

The simulation was executed utilizing a coronary artery disease dataset in training, testing, and predicting Ischemic Heart Disease, which was retrieved from [28]. Besides, snapshots of the following were taken during the simulation process, such as the used dataset, designed BBN model for predicting Ischemic Heart Disease, Cardiovascular Diseases and its manifestations, BBN model convergence chart, loglikelihood batch query chart, feature importance of nodes chart, in-sample anomaly detection chart, likelihood plots of ailments being the cause of Cardiovascular Diseases and Ischemic Heart Disease, loglikelihood graph for detecting Ischemic Heart Disease and Cardiovascular Diseases, and likelihood against loglikelihood plot for predicting Ischemic Heart Disease and Cardiovascular Diseases which appear 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 a mix of ailment afflictions, and factors amounting to 92 taken into consideration in the prediction of Ischemic Heart Disease and Cardiovascular Diseases with each sickness and factor having a value that addresses the probability of such ailment malady, and factor causing Ischemic Heart Disease and Cardiovascular Diseases. The ailments and factors that aids prediction of Ischemic Heart Disease and Cardiovascular Diseases are: Abnormal Heartbeat, Abnormal Inflammatory Cells, Acute Heart Failure, Age < 70, Abnormal Speech, Angina, Autoimmune Diseases, Back Pain, Blood In The Urine, Blue-Tinted Skin, Blurred Vision, Breathlessness, Build-Up of Plaque, Calcium Phosphate, Calf Muscle Cramps, Cardiovascular Diseases, Cardiovascular System Strain, Cerebrovascular Diseases, Chronic Heart Failure, Coldness of Feet, Congenital Heart Disease, Cough, Deep Vein Thrombosis, Depression, Diabetes, Dizziness, Erectile Dysfunction, Excess Weight, Family History, Fast Heartbeat, Fatigue, Female, Fever, Flushing, Heart Attack, Heart Failure, Heart Muscle Damage, Heavy Alcohol Use, High Cholesterol, High Level Homocysteine, High Protein in Urine, High Sensitivity C-Reactive Protein, High Stress, Hip Cramps, High Triglycerides, Hypertension, Inconsistent Breathing, Inflammatory Conditions, Ischemic Heart Disease, Jaw Pain, Leg Colour Change, Leg Numbness, Loss of Appetite, Low Density Lipoprotein, Lupus, Male, Memory Loss, Migraine, Myalgia, Myocardial Infarction, Nausea, Narrowed Arteries, Neck Pain, Nosebleeds, Obesity, Paralysis, Peripheral Artery Disease, Preeclampsia, Pulmonary Embolism, Physical

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Inactivity, Rash, Rheumatic Heart Disease, Rheumatoid Arthritis, Severe Angina, Sex, Sleep Apnea, Smoking, Sore Throat, Sores on Legs, Speech Loss, Stable Angina, Stomach Pain, Stroke, Sweating, Swollen Legs, Sudden Cardiac Death, Thigh Cramps, Tobacco Use, Type-2 Diabetes, Unhealthy Diet, Unstable Angina and Weak Pulse In Legs respectively.

Figure 2 below shows a snapshot of the dataset utilized in training, testing, and predicting Ischemic Heart Disease, Cardiovascular Diseases (CVDs), and their symptoms.

Hypertension	Inconsistent Breathing	Inflammatory Conditions	Ischemic Heart Disease	Jaw Pain	Leg Colour	Leg Numbness	Loss of Appetite
0.887	0.156	-0.388	2.09	-1.41	0.0635	1.12	-0.0689
-1.01	0.341	-0.49	2.08	-1.38	1.16	-0.213	-0.239
1.54	-0.936	-1.18	2.02	-0.344	1.07	-0.417	1.37
-0.592	-0.339	0.599	1.55	2.09	-0.0967	-0.644	0.433
0.663	0.495	-0.356	1.39	1.19	1.54	-0.33	-0.643
-0.131	-1.94	-0.408	1.38	-2.29	0.957	-0.879	-1.71
-0.395	0.903	0.944	1.37	-0.638	-0.503	-0.646	-0.478
-0.191	-0.0701	-0.485	1.31	0.479	0.667	1.2	-2.04
0.564	-0.326	1.15	1.29	0.625	0.392	-1.03	1.75
-0.989	0.125	-0.971	1.24	0.217	2.07	-0.00921	-1.89
0.036	-1.64	0.638	1.18	-0.59	-0.754	0.117	-0.684
0.0421	-1.06	-0.407	1.1	-0.778	-1.35	-0.592	0.126
1.05	0.337	-1.2	1.09	1.41	2.37	-0.873	-1.2
0.467	-0.362	-1.57	1.05	0.468	-1.13	1.61	1.96
1.72	-0.641	0.572	1.05	0.696	0.123	0.0937	0.577
-0.277	1.48	-0.906	0.879	-0.854	0.951	0.502	-0.114
1.38	0.351	-0.582	0.868	1.61	-0.0645	-2.76	0.303
-0.862	1.47	-0.881	0.77	1.08	0.246	-1.31	-0.329
-1.16	-0.274	-0.178	0.666	-0.573	1.43	-0.0738	-1.13
0.0936	-0.118	0.952	0.653	-0.575	-0.0607	-0.968	1.25
-0.375	1.16	-0.516	0.594	-1.46	0.0509	0.928	0.16
0.352	0.298	-0.563	0.588	-0.513	-0.28	0.582	-1.05
1.05	1.33	0.275	0.456	1.77	2.48	0.0736	0.27
-0.666	-0.0991	0.0218	0.341	-1.31	0.142	0.458	1.76

Figure 2: Snapshot of Dataset

The Bayes-Server platform was used to design the Bayesian Belief Network model. Nevertheless, the Bayesian Belief Network (BBN) for predicting Ischemic Heart Disease (IHD), Cardiovascular Diseases (CVDs) and their symptoms was built with the end goal that the nodes on the network are connected dependent on the likelihood of an ailment coming about to another and factor affecting another factor. In our model for a case to be meant as an Ischemic Heart Disease infection case, the ailments and different components taken into cognizance in the diagnosis of Ischemic Heart Disease are: Abnormal Heartbeat, Abnormal Inflammatory Cells, Acute Heart Failure, Age < 70, Abnormal Speech, Angina, Autoimmune Diseases, Back Pain, Blood In The Urine, Blue-Tinted Skin, Blurred Vision, Breathlessness, Build-Up of Plaque, Calcium Phosphate, Calf Muscle Cramps, , Cardiovascular System Strain, Chronic Heart Failure, Coldness of Feet, Cough, Depression, Diabetes, Dizziness, Erectile Dysfunction, Excess Weight, Family History, Fast Heartbeat, Fatigue, Female, Fever, Flushing, Heart Attack, Heart Failure, Heart Muscle Damage, Heavy Alcohol Use, High Cholesterol, High Level Homocysteine, High Protein in Urine, High Sensitivity C-Reactive Protein, High Stress, Hip Cramps, High Triglycerides, Hypertension, Inconsistent Breathing, Inflammatory Conditions, Ischemic Heart Disease, Jaw Pain, Leg Colour Change, Leg Numbness, Loss of Appetite, Low Density Lipoprotein, Lupus, Male, Memory Loss, Migraine, Myalgia, Myocardial Infarction, Nausea, Narrowed Arteries, Neck Pain, Nosebleeds, Obesity, Paralysis, Preeclampsia, Pulmonary Embolism, Physical Inactivity, Rash, Rheumatoid Arthritis, Severe Angina, Sex, Sleep Apnea, Smoking, Sore Throat, Sores on Legs, Speech Loss, Stable Angina, Stomach Pain, Stroke, Sweating, Swollen Legs, Sudden Cardiac Death, Thigh Cramps, Tobacco Use, Type-2 Diabetes, Unhealthy Diet, Unstable Angina and Weak Pulse In Legs respectively.

Figure 3 shows the BBN model for detecting Ischemic Heart Disease (IHD), Cardiovascular Disease (CVDS) and their symptoms.

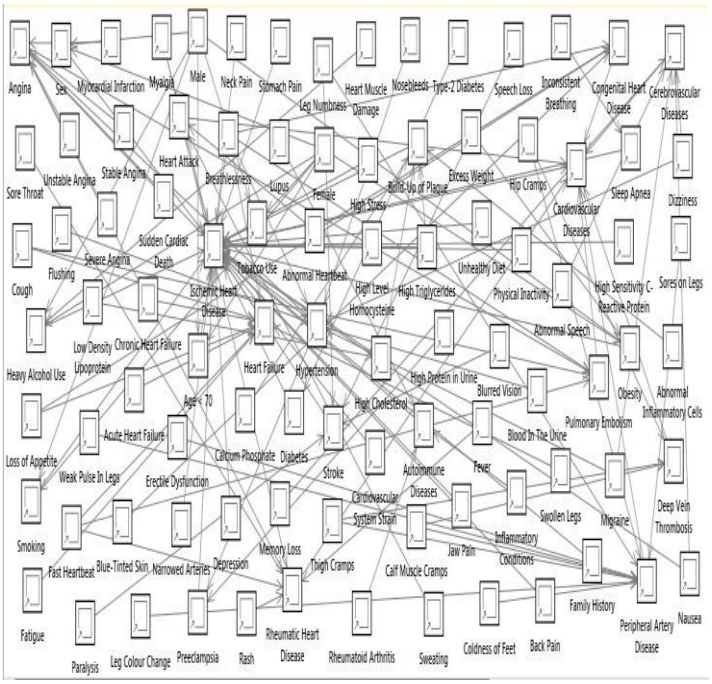

Figure 3: Bayesian Belief Network Model for Detecting Ischemic Heart Disease (IHD), Cardiovascular Disease (CVDS) and Their Symptoms

So, to mathematically represent our model we have:
Ischemic Heart Disease

$$\%_{i=1}^{92} P(Disease_i) \mid Parents_i(Disease_i) \qquad (2)$$

Where,
Disease: Node with a Disease Ailment
Parents ($Disease_i$) = Nodes that converge on Disease $Ailment_i$.
The training and testing process of the BBN model in figure 3 employed the dataset in figure 2. Upon completion of training and testing the BBN model, the test data converged at time series 2. As the simulation process progressed, the attained loglikelihood and likelihood values for all cases were recorded and can be viewed in figure 5.

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Figure 4 below shows the BBN model convergence of Ischemic Heart Disease (IHD) and its symptoms at Iteration Count 2.

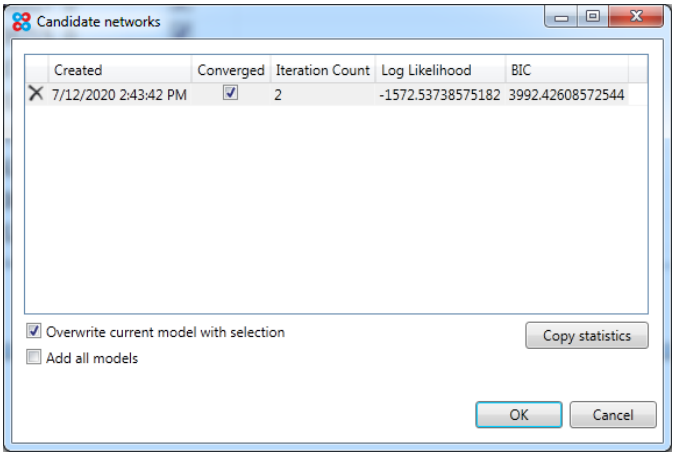

Figure 4: Bayesian Belief Network Model for Detecting Ischemic Heart Disease (IHD) Converging at Time Series 2.

Figures 4, 5, 6, 7, 8, 9 ,10, 11 and 12 shows loglikelihood batch query chart for predicting Ischemic Heart Disease (IHD), Cardiovascular Disease (CVDs) and their symptoms, feature importance chart of nodes in the BBN model, the in-sample anomaly detection chart, the likelihood plot of Heart Diseases and symptoms prompting Cardiovascular Diseases infection case and its probabilities, the likelihood plot of Build-Up Plaque, Narrowed Arteries and Cardiovascular Diseases and their symptoms prompting an Ischemic Heart Disease infection case and its probabilities, the loglikelihood graph for detecting Ischemic Heart Disease, Cardiovascular Disease (CVDs) with their symptoms; and, likelihood against loglikelihood for predicting Ischemic Heart Disease and Cardiovascular Disease (CVDs) with their symptoms respectively. The results generated from the simulation demonstrated that the system had the option to anticipate 99% Ischemic Heart Disease and Cardiovascular Disease (CVDs) on the dataset precisely, and it had a loglikelihood of 103.99 on the test dataset.

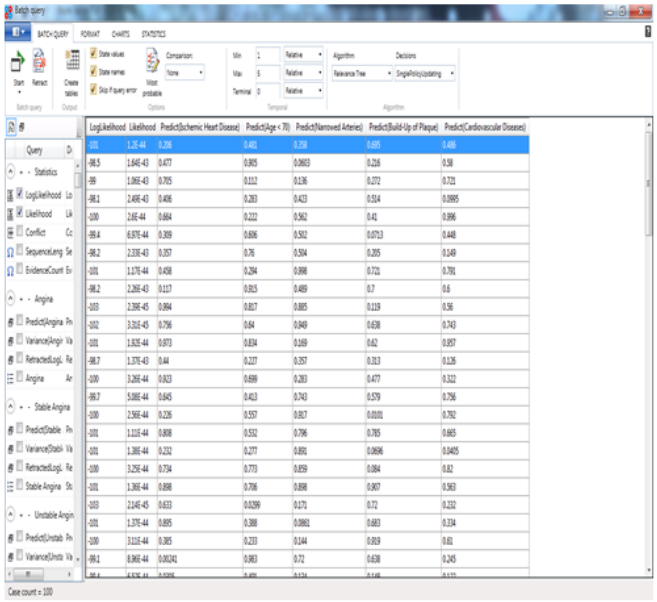

Figure 5: The Loglikelihood Batch Query Chart for Predicting Ischemic Heart Disease and Cardiovascular Disease (CVDs) with Their Symptoms.

This loglikelihood batch query chart shows the outcome of the deployment of the test data. Here, 100 experimental cases were conducted, and the results produced from the test data showcased the system's capability to predict the probability for each case of Ischemic Heart Disease, Cardiovascular Diseases and their symptoms with the loglikelihood and likelihood (probability values within 0 to 1) obtained from each of the 100 experimental cases and recorded as follows:

In Experiment 1: The probability of Predict(Ischemic Heart Disease) was 0.206, Predict(Age < 70) was 0.481, Predict(Narrowed Arteries) was 0.358, Predict(Build-Up Plaque) was 0.695 and Predict(Cardiovascular Diseases) was 0.486 in experiment 1 compared to 0.206003104, 0.48100022, 0.3580100332, 0.694701221 and respectively in the test data. Furthermore, Experiment 1 had 20.6%, 48.10%, 35.8%, 69.5%, and 48.6% sensitivity of Ischemic Heart Disease, Cardiovascular Diseases and their symptoms after termination of Experiment 1 correspondingly.

In Experiment 2: The probability of Predict(Ischemic Heart Disease) was 0.477, Predict(Age < 70) was 0.905, Predict(Narrowed Arteries) was 0.0603, Predict(Build-Up Plaque) was 0.216 and Predict(Cardiovascular Diseases)was 0.58 in experiment 2 compared to 0.477001402, 0.905010143,0.060281003, 0.216011450 and respectively in the test data. Furthermore, Experiment 2 had 47.7%, 90.50%, 6.3%, 21.6% and 58% sensitivity of Ischemic Heart Disease, Cardiovascular Diseases and their symptoms after due conclusion of Experiment 2 respectively.

In Experiment 3: The probability of Predict(Ischemic Heart Disease) was 0.705, Predict(Age < 70) was 0.112, Predict(Narrowed Arteries) was 0.136, Predict(Build-Up

Plaque) was 0.272 and Predict(Cardiovascular Diseases)was 0.721 in experiment 3 compared to 0.704601311,0.112010021,0.136002000, 0.272700011 and respectively in the test data. Furthermore, Experiment3 had 70.5%, 11.2%, 13.6%, 27.2% and 72.1% sensitivity of Ischemic Heart Disease, Cardiovascular Diseases and their symptoms after completion of experiment 3 in that order. Furthermore, 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 Cardiovascular Disease (CVDs) with its symptoms in figure 3 above.

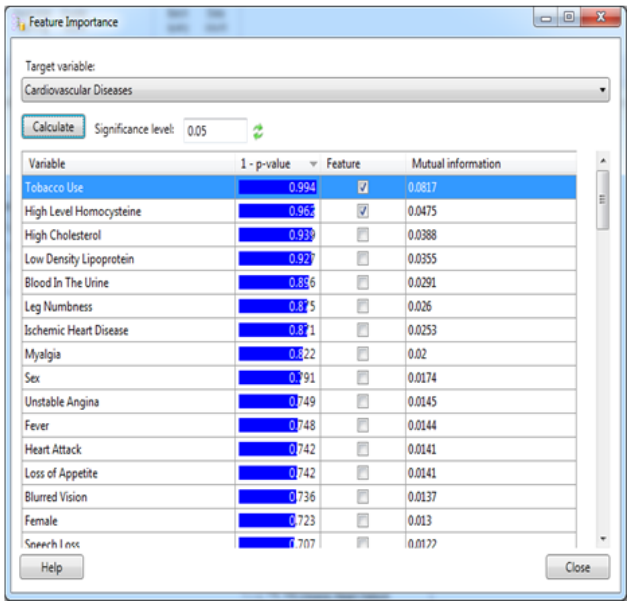

Figure 6. The Feature Importance Chart for Cardiovascular Diseases Node in the Designed BBN Model

The Feature Importance Chart shows the p-value of the variable (nodes), Feature, and Mutual information in about the Cardiovascular Diseases node.
The p-value signifies the likelihood (probability) of the nodes being the cause of a Cardiovascular Disease infection.
The Feature Checkbox is enabled if that particular node is fully involved in the cause of a Cardiovascular Disease infection.
The Mutual Information shows the relationship with nodes directly connected (i.e., in this case, the direct relationship of the nodes with the Cardiovascular Disease node) and assigned a value.
The Significance Level signifies the margin of error in the detection of Cardiovascular Diseases.
Ischemic Heart Disease and its symptoms in figure 3.

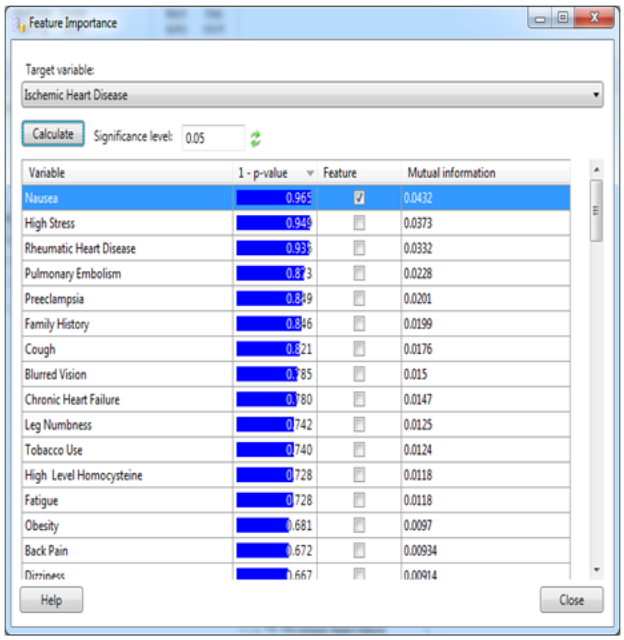

Figure 7. The Feature Importance Chart for Ischemic Heart Disease Node in the BBN Model

The Feature Importance Chart shows the p-value of the variable (nodes), Feature and Mutual information in allusion to the target variable which is the Ischemic Heart Disease node.
The p-value signifies the likelihood (probability) of the nodes being the cause of a target variable (Ischemic Heart Disease) infectivity.
The Feature checkbox is enabled if that particular node is fully involved in the cause of a target variable (Ischemic Heart Disease) contagion.
The Mutual information shows the relationship with nodes directly connected (i.e., in this case, the direct relationship of the nodes with the Ischemic Heart Disease node) and assigned a value.
The Significance Level signifies the margin of error in the detection of target variable (Ischemic Heart Disease).

Figure 8 below shows the in-sample anomaly detection chart of the designed BBN model in figure 3.

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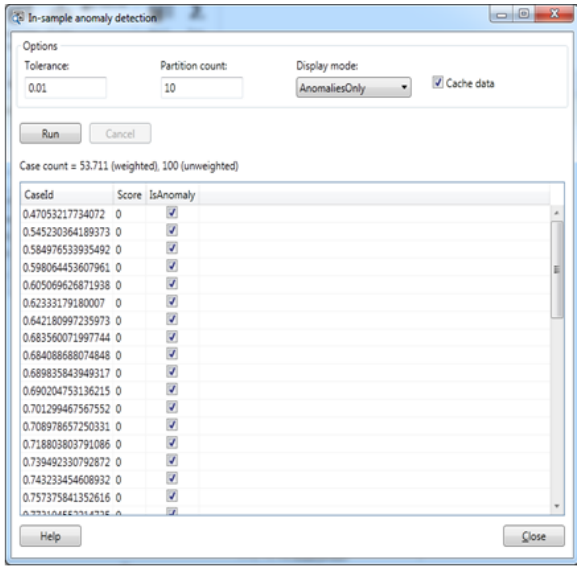

Figure 8. The In-sample Anomaly Detection Chart of BBN Model

The In-sample Anomaly Detection Chart shows 100 test consequences of distinguishing Ischemic Heart Disease and Cardiovascular Diseases. Each Case is assigned an ID(Identification value) which are estimations of the Predict(Ischemic Heart Disease), Predict(Age < 70), Predict(Narrowed Arteries), Predict(Build-Up Plaque) and Predict(Cardiovascular Diseases) in figure 5.

The IsAnomaly checkbox is enabled to recognize that each case is an affirmed instance Ischemic Heart Disease and Cardiovascular Disease ailments with their side-effects. The 100 cases include Ischemic Heart Disease and Cardiovascular Diseases with their side-effects having case tally estimation of 53.711 (weighted), which implies the significance of the cases prompting Ischemic Heart Disease and Cardiovascular Diseases infections. On the other hand, the 100 unweighted signifies the number of cases in the pool of information accessible to the system for recognition of Ischemic Heart Disease, Cardiovascular Diseases and their manifestations in the dataset pool. The tolerance is the margin of error that could be encountered as regards to the detection of the Ischemic Heart Disease, Cardiovascular Diseases and their symptoms.

Figure 9 below shows the likelihood plot of Heart diseases and its symptoms prompting Cardiovascular Diseases.

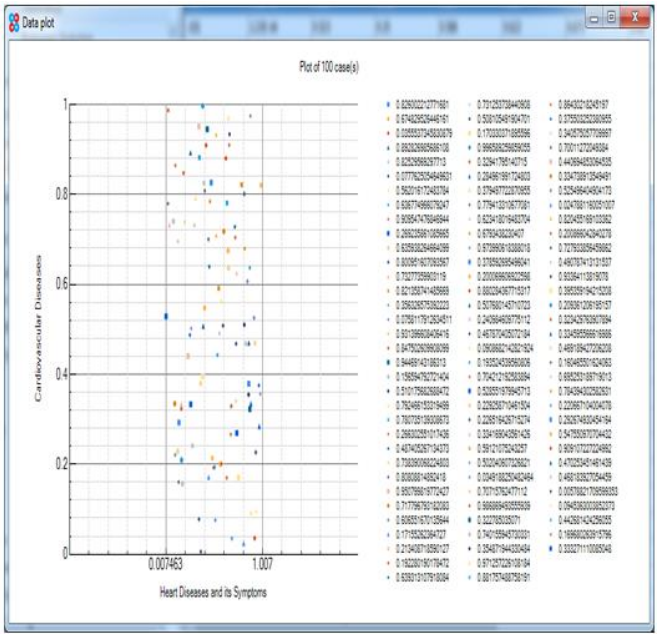

Figure 9. The Likelihood Plot of Heart Diseases Ailments and Symptoms Prompting Cardiovascular Diseases

The likelihood plot shows the probability of Heart disease ailments and after-effects of infections prompting a Cardiovascular Disease infection case. In this plot, 100 experiments were pondered 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 0.007463 to 1.007 on X-axis and positioned on the privilege of the plot. The variable marked "Cardiovascular Diseases" is located on the Y-axis is plotted against another variable named "Heart Diseases and its symptoms" stationed on the X-axis. Nevertheless, from this plot, there are five investigative classes of Cardiovascular Disease cases in which our system had the choice to distinguish; they are asymptomatic, mild, moderate, severe, and critical classes in the order above.

Asymptomatic Class: This class likelihood ranges from 0 to 0.2 on Y-axis and 0.007463 to 1.007 on X-axis. This area has 17 colored points (cases), which infers 17 cases of no Cardiovascular Disease infection by any stretch of the imagination; thus, this class of patients is categorized as being Asymptomatic.

Mild Class: This class likelihood ranges from 0.2 to 0.4 on Y-axis and 0.007463 to 1.007 on X-axis. This zone has 24 tinted points (cases), which correspond to 24 occurrences of patients with Cardiovascular Disease infectivity with the severity level classified as being Mild.

Moderate Class: This class likelihood ranges from 0.4 to 0.6 on Y-axis and 0.007463 to 1.007 on X-axis. This zone has 17 tinted points (cases), which infers 17 examples of patients with Cardiovascular Disease infection with the seriousness level classified as being Moderate.

Severe Case: This class likelihood ranges from 0.6 to 0.8 on Y-axis and 0.007463 to 1.007 on X-axis. This locale has 22 toned points (cases), which implies 22 occurrences of

patients with Cardiovascular Disease contagion with the seriousness level recognized as being Severe.

Critical Class: This class likelihood spans from 0.8 to 1 on Y-axis and 0.007463 to 1.007 on X-axis. This region has 20 toned points (cases), which connotes 20 occurrences of patients with Cardiovascular Disease infectivity 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 essential probability estimation of heart diseases and after-effects of diseases prompting Cardiovascular Disease infection reported to be 0.996589259859055 which is very well below 1.

Of the 100 experimental cases, the system anticipated 100 cases of Heart diseases and after-effects of diseases prompting a Cardiovascular Disease infection case extending from asymptomatic, mild, moderate, severe, and critical classes precisely from the test data with 99.66% sensitivity of Cardiovascular Diseases.

Figure 10 below shows the likelihood plot of build-up plaque, narrowed arteries, and cardiovascular disease symptoms prompting Ischemic Heart Disease infection case.

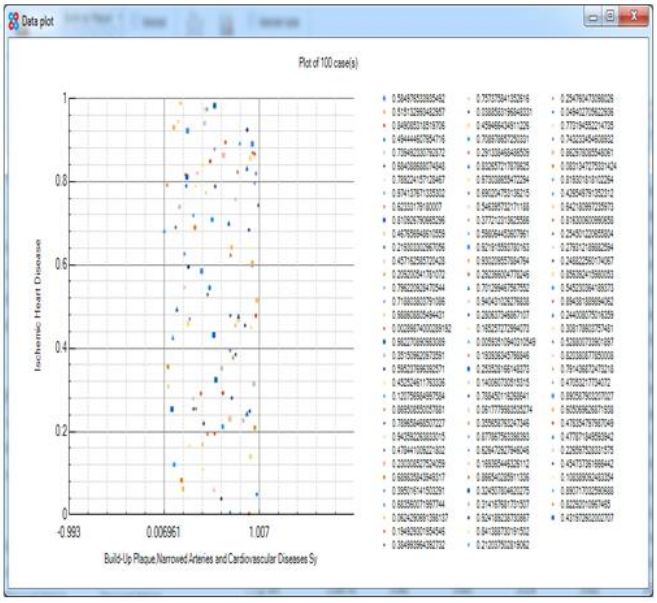

Figure 10. The Likelihood Plot of Build-Up Plaque, Narrowed Arteries, and Cardiovascular Diseases Symptoms Prompting an Ischemic Heart Disease.

The likelihood plot shows the probability of build-up plaque, narrowed arteries and cardiovascular diseases symptoms prompting Ischemic Heart Disease infectivity case. In this plot, 100 experiments were analyzed with each colored point in the chart named a case and allocated a probabilistic value which is in the scope of 0 to 1 on Y-axis and 0.02818 to 1.028 on X-axis and positioned on the privilege of the plot. The variable named "Ischemic Heart Disease" is located on the Y-axis is plotted against another variable marked "Build-Up Plaque, Narrowed Arteries and Cardiovascular Diseases Symptoms" sited on the X-axis. All things being equal, from this plot, there are five diagnostic classes of Ischemic Heart Disease cases which our system had the option to identify; they are asymptomatic, mild, moderate, severe, and critical classes separately.

Asymptomatic Class: This class likelihood ranges from 0 to 0.2 on Y-axis and 0.006961 to 1.007 on X-axis. This region has 14 tinted points (cases), which infers 14 cases of no Ischemic Heart Disease infection case in any capacity; with this class of patients is categorized as being Asymptomatic.

Mild Class: This class likelihood ranges from 0.2 to 0.4 on Y-axis and 0.006961 to 1.007 on X-axis. This locale has 22 colored points (cases), which suggests 22 instances of patients with Ischemic Heart Disease infectivity with the severity level inferred as being Mild.

Moderate Class: This class likelihood ranges from 0.4 to 0.6 on Y-axis and 0.006961 to 1.007 on X-axis. This locale has 20 tinted points (cases), which signifies 20 cases of patients with Ischemic Heart Disease infection with the severity level deduced as being Moderate.

Severe Case: This class likelihood ranges from 0.6 to 0.8 on Y-axis and 0.006961 to 1.007 on X-axis. This region has 19 tinted points (cases), which represent 19 cases of patients with Ischemic Heart Disease infection with the seriousness level classified as being Severe.

Critical Class: This class likelihood from 0.8 to 1 on Y-axis 0.006961 to 1.007 on X-axis. This locale has 25 hued points (cases), which suggests 25 instances of patients with Ischemic Heart Disease infection with the severity level inferred as being Critical.

All 100 cases in figure 10 had probability values less than or equal to 1, with the most noteworthy probability estimation of build-up plaque, narrowed arteries and cardiovascular diseases symptoms prompting Ischemic Heart Disease infection ascertained to 0.988608805494431 which is less than 1.

Of the 100 trial cases, the system anticipated 100 instances of build-up plaque, narrowed arteries, and cardiovascular diseases symptoms prompting Ischemic Heart Disease infection case extending from asymptomatic, mild, moderate, severe, and critical classes precisely from the test data with 98.88% sensitivity of Ischemic Heart Disease.

With the severity level of Ischemic Heart Disease and Cardiovascular Diseases already attained, we intend to plot the chart for the loglikelihood graph for detecting Ischemic Heart Disease and Cardiovascular Diseases ailments; likelihood against loglikelihood graph for foreseeing Ischemic Heart Disease and Cardiovascular Diseases; and unravel the loglikelihood value for distinguishing Ischemic Heart Disease, Cardiovascular Diseases, and prediction exactness of the BBN model which will be discussed in figure 11 and 12 beneath.

Figure 11 shows the loglikelihood chart for detecting Ischemic Heart Disease and Cardiovascular Diseases.

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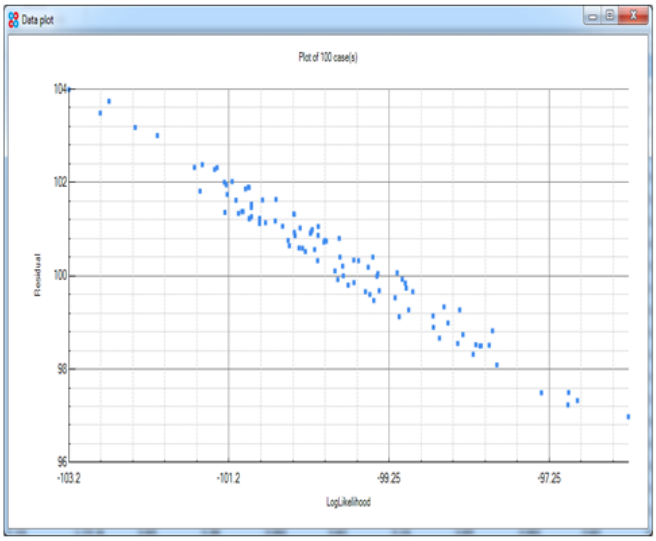

Figure 11. Loglikelihood Chart for Detecting Ischemic Heart Disease and Cardiovascular Diseases.

This loglikelihood graph for detecting Ischemic Heart Disease and Cardiovascular Diseases shows residual values on the Y-axis plotted against the loglikelihood esteem on the X-axis which are independent factors. A residual value is an extent of how much a regression line perpendicularly misses a data spot. Quintessentially, regression lines are the paramount assault of a ton of information. The lines are structured as midpoints; a few data spots will match the line and others will fail hit the spot. In this graph, it shows that 100 preliminary cases achieved estimation of 103.99, 103.79, 103.63, 103.24, 103.15, 102.25, 102.24, 102.20, 102,101.98… 97.25, 97.20 exclusively.

Then again, residual values should be similarly and subjectively isolated around the level lines. Taking a viewpoint on the system' exploratory results regards procured from the even lines on the outline, it might be seen that where the most raised residual esteem and the loglikelihood independent factor accomplished congregates at -103.2 on horizontal line with 104 being the most imperative value that can be reached on the vertical line. The residual value achieved is 103.99 and loglikelihood independent esteem is -103.2, the differentiation between the two characteristics is 0.79 which is the complexity between the estimations of the prediction outcomes and unique test data of 100% in figure 5.

Thus, the attained Loglikelihood value for recognizing Ischemic Heart Disease and Cardiovascular Diseases is 103.99.

Figure 12 shows the likelihood against loglikelihood for predicting Ischemic Heart Disease, Cardiovascular Diseases and their symptoms of the designed BBN model in figure 3.

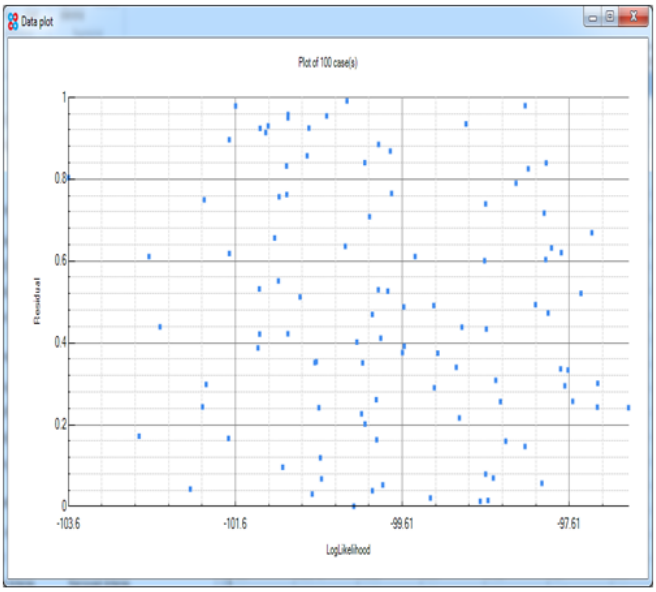

Figure 12. The Likelihood against the Loglikelihood Graph for Predicting Ischemic Heart Disease, Cardiovascular Diseases and their Symptoms

This likelihood against loglikelihood plot for Ischemic Heart Disease and Cardiovascular Diseases with its symptoms shows the residual (likelihood) on the Y-axis plotted against the Loglikelihood on the X-axis both of which are independent variables. However, the likelihood of events (Predicting Ischemic Heart Disease and Cardiovascular Diseases) occurring are probabilistic values placed between 0 and 1. In this plot, 100 exploratory cases were conducted which achieved the estimations of 0.9999, 0.9997, 0.9996, 0.9994, 0.9990, 0.001,….0.0001,0 individually. In any case, residual (likelihood) values ought to be reliably and capriciously spread around the level lines. Basically, seeing the system' exploratory results acquired from the level lines on the diagram, it will in general be seen that the residual probability value attained is 0.9999 and loglikelihood independent value is –103.6.

Accordingly, in this system, the most essential likelihood esteem that can be accomplished is 1. With 1, being the 100 % residual (probability) rate mark, to get our exactness precision rate, we divide attained likelihood probability esteem by highest likelihood value that can be attained and increase by most imperative residual mark, that is 0.9999/1*100% = 99.99% forecast exactness rate on the test data.

In addition, the Likelihood graphs in figure 9, 10 showed all classes of severity status of heart diseases and symptoms leading to cardiovascular disease case; build-up plaque, narrowed arteries and cardiovascular disease symptoms prompting Ischemic Heart Disease ranging from asymptomatic, mild, moderate, severe, and critical classes individually with their probabilities while figure 11 demonstrated the system loglikelihood estimation of 103.99 for distinguishing Ischemic Heart Disease and Cardiovascular Diseases and their signs, while the likelihood

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against loglikelihood expectation plot of Ischemic Heart Disease, Cardiovascular Diseases and their indications in figure 12 established the 99.99% forecast precision of the system.

Be that as it may, the likelihood given there is evidence of heart disease and its after-effects prompting a Cardiovascular Disease case and its symptoms is denoted as: P(Cardiovascular Diseases| Abnormal Heartbeat, Abnormal Inflammatory Cells, Acute Heart Failure, Age < 70, Abnormal Speech, Angina, Autoimmune Diseases, Back Pain, Blood In The Urine, Blue-Tinted Skin, Blurred Vision, Breathlessness, Build-Up of Plaque, Calcium Phosphate, Calf Muscle Cramps, Cardiovascular Diseases, Cardiovascular System Strain, Cerebrovascular Diseases, Chronic Heart Failure, Coldness of Feet, Congenital Heart Disease, Cough, Deep Vein Thrombosis, Depression, Diabetes, Dizziness, Erectile Dysfunction, Excess Weight, Family History, Fast Heartbeat, Fatigue, Female, Fever, Flushing, Heart Attack, Heart Failure, Heart Muscle Damage, Heavy Alcohol Use, High Cholesterol, High Level Homocysteine, High Protein in Urine, High Sensitivity C-Reactive Protein, High Stress, Hip Cramps, High Triglycerides, Hypertension, Inconsistent Breathing, Inflammatory Conditions, Ischemic Heart Disease, Jaw Pain, Leg Colour Change, Leg Numbness, Loss of Appetite, Low Density Lipoprotein, Lupus, Male, Memory Loss, Migraine, Myalgia, Myocardial Infarction, Nausea, Narrowed Arteries, Neck Pain, Nosebleeds, Obesity, Paralysis, Peripheral Artery Disease, Preeclampsia, Pulmonary Embolism, Physical Inactivity, Rash, Rheumatic Heart Disease, Rheumatoid Arthritis, Severe Angina, Sex, Sleep Apnea, Smoking, Sore Throat, Sores on Legs, Speech Loss, Stable Angina, Stomach Pain, Stroke, Sweating, Swollen Legs, Sudden Cardiac Death, Thigh Cramps, Tobacco Use, Type-2 Diabetes, Unhealthy Diet, Unstable Angina and Weak Pulse In Legs) = 0.996589259859055

On the other hand, the likelihood given there is evidence of build-up plaque, narrowed arteries and cardiovascular disease, and its after-effects prompting an Ischemic Heart Disease case and its symptoms is denoted as: P(Ischemic Heart Diseases| Abnormal Heartbeat, Abnormal Inflammatory Cells, Acute Heart Failure, Age < 70, Abnormal Speech, Angina, Autoimmune Diseases, Back Pain, Blood In The Urine, Blue-Tinted Skin, Blurred Vision, Breathlessness, Build-Up of Plaque, Calcium Phosphate, Calf Muscle Cramps, , Cardiovascular System Strain, Chronic Heart Failure, Coldness of Feet, Cough, Depression, Diabetes, Dizziness, Erectile Dysfunction, Excess Weight, Family History, Fast Heartbeat, Fatigue, Female, Fever, Flushing, Heart Attack, Heart Failure, Heart Muscle Damage, Heavy Alcohol Use, High Cholesterol, High Level Homocysteine, High Protein in Urine, High Sensitivity C-Reactive Protein, High Stress, Hip Cramps, High Triglycerides, Hypertension, Inconsistent Breathing, Inflammatory Conditions, Ischemic Heart Disease, Jaw Pain, Leg Colour Change, Leg Numbness, Loss of Appetite, Low Density Lipoprotein, Lupus, Male, Memory Loss, Migraine, Myalgia, Myocardial Infarction, Nausea, Narrowed Arteries, Neck Pain, Nosebleeds, Obesity, Paralysis, Preeclampsia, Pulmonary Embolism, Physical Inactivity, Rash, Rheumatoid Arthritis, Severe Angina, Sex, Sleep Apnea, Smoking, Sore Throat, Sores on Legs, Speech Loss, Stable Angina, Stomach Pain, Stroke, Sweating, Swollen Legs, Sudden Cardiac Death, Thigh Cramps, Tobacco Use, Type-2 Diabetes, Unhealthy Diet, Unstable Angina and Weak Pulse In Legs = 0.988608805494431.

From the test, it will in general be seen that our model has a higher residual loglikelihood value which is 103.99, an overall prediction precision of 99.99%; 98.86% and 99.66% sensitivity of Ischemic Heart Disease and Cardiovascular Diseases in that order.

In the end, comparing the 99.99% forecast precision of our model with the works conducted by [6, 7, 11, 12, 14, 15, 16, 17, 18, 19, 20, 21, 23, 24 and 25] which had 78.2%, 94%, 92%, 92%, 69.51%, 92%, 92.8%, 73.78%;(80.14%, 89.12%, 77.78%,96.72%),81.82%,93.3%,94.5%,72.6%, 94.91%, and 79.5% identification exactness individually. It is clear our model has superior prediction exactness than the previously mentioned systems. The higher forecast exactness achieved by our model could be a direct result of the range of the dataset used in training and testing the model similarly as its ability to foresee the covering symptoms of Ischemic Heart Disease and Cardiovascular Disease infections, from this time forward helping the high recognition exactness of the abovementioned diseases.

5. Conclusion and Future Scope

Ischemic Heart Disease is a terrifying cardiovascular disease that truncates the flow of blood to the heart muscles due to plaques resident in the blood which solidifies thus slandering the arteries. In recent past, several strategies have been employed in diagnosing Ischemic Heart Disease with the solitary objective of curbing the untimely deaths of patients due to late diagnosis and misdiagnosis of the aforesaid disease, an area health and Information Technology experts are making tremendous attempts to enhance.

In this paper, we utilized an AI strategy called Bayesian Belief Network to predict Ischemic Heart Disease, Cardiovascular Diseases and their symptoms. The model had 92 nodes with each node addressing a select ailment and factors that influence diagnosis of Ischemic Heart Disease, Cardiovascular Diseases and their symptoms. The model was trained and tested and had a general prediction accuracy of 99.99% and a loglikelihood estimation of 103.99 in predicting Ischemic Heart Disease, Cardiovascular Diseases infections with their side-effects; 98.86% and 99.66% sensitivity Ischemic Heart Disease, Cardiovascular Diseases in a that order.

We can surmise that the acquired results exhibited the learning capacity of the BBN model, despite the fact that

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the data utilized can be improved appreciably. In this paper, we concentrated on the symptoms of Ischemic Heart Disease, Cardiovascular Diseases which supported the model' inference mechanism for early diagnosis of the aforementioned maladies.

For future works, there is need to incorporate more information inclined by the infection in other to improve the prescient and derive optimal outcomes which will be utilized and lead to an improvement in the accompanying areas: forecast of Ischemic Heart Disease, Cardiovascular Diseases and their symptoms, the discovery of Ischemic Heart Disease, Cardiovascular Diseases and their side-effects.

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Authors Profile

Mr. Solomon Osarumwense Alile obtained a Diploma in Data Processing degree from University of Benin in 2004, B.Sc. degree in Computer Science in 2012 from Lagos State University (LASU), Ojo, Lagos and M.Sc in Computer Science from University of Benin in 2019. He is a Cisco Certified Network Associate (Routing and Switching) and System Engineer. He is a member of International Computer Science and Engineering Society (ICSES), Institute For Engineering Research and Publication (IFERP), International Association of Engineers (IAENG), International Association of Engineers Society of Computer Science (ISCS), International Association of Engineers Society of Wireless Networks (ISWN), International Association of Engineers Society of Scientific Computing (ISSC), International Association of Engineers Society of Internet Computingand Web Services (ISICWS), International Association of Engineers Society of Information System Engineering (ISISE), International Association of Engineers Society of Data Mining (ISDM), International Association of Engineers Society of Artificial Intelligence (ISAI), and International Association of Engineers Society of Software Engineering (ISSE). He has published more than 12 research papers in reputed international journals which covers the area of cybersecurity and application of artificial intelligence in health diagnosis, all of which are available online. His skills are Machine Learning, Supervised Learning, Computer Networking, Routing and Switching and Network Security. His area of interest includes Information Technology, Machine Learning and Cybersecurity. He is currently conducting research works in the area of cybersecurity and development of AI Based Systems.

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