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PATIENT FACING SYSTEMS

Development of Big Data Predictive Analytics Model for Disease Prediction using Machine learning Technique

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Abstract

Now days, health prediction in modern life becomesvery much essential. Big data analysis plays a crucial role to predict future status of healthand offerspreeminenthealth outcome to people. Heart disease is a prevalent disease cause's death around the world. A lotof research is going onpredictive analytics using machine learning techniques to reveal better decision making. Big data analysis fosters great opportunities to predict future health status from health parameters and provide best outcomes. WeusedBig Data Predictive Analytics Model for Disease Prediction using Naive Bayes Technique (BPA-NB). It providesprobabilistic classification based on Bayes' theorem with independence assumptions between the features. Naive Bayes approach suitable for huge data sets especially for bigdata. The Naive Bayes approachtrain the heart disease data taken from UCI machine learning repository. Then, it was making predictions on the test data to predict the classification. The results reveal that the proposed BPA-NB scheme providesbetter accuracy about 97.12% to predict the disease rate. The proposed BPA-NB scheme used Hadoop-spark as big data computing tool to obtain significant insight on healthcare data. The experiments are done to predict different patients' future health condition. It takes the training dataset to estimate the health parameters necessary for classification. The results show the early disease detection to figure out future health of patients.

Keywords Big data · Machine learning · Prediction · Naive Bayes · SparkFramework

Introduction

The national and international databases were examined to identify studies conducted about big data analytics in healthcare, heart attack prediction and prevention (Salma and suma [1]). Now a day, Big Data analytics play a vital role in predicting heart attack and tailoring of treatment for cardiovascular disease. Big Data (Lidong and Cheryl [2]) provide 360 degree view of patients' data to perform analytics for better predict outcomes. Prediction of healthcare increases the accuracy of diagnosis and helps to preventive medicine and public health. Predictive analytics with bigdata [3, 4] allow researchers to develop prediction models that do not require thousands of cases and that become more accurate over time. This work usesNaive Bayes classification techniqueto buildan accuracy predictive modelas it is one of the most commonly applied machines learning technique. Besides, diseases like heart illnessesoccur when vital health parameters become anomalous. Hence, predictions of abnormal health parameters are required to improve the health status for improve the quality life. Naïve Bayes technique plays an important role to predict health labels from the obtained dataset. Predicting heart disease is hard to resolve it to improve the health status. Henceforth, it is very much essential to design an effective technique to predict the health status from the health parameters. A few techniques have been proposed in related works section to analyze and predict the health status of the patients.

The contributions of the proposed work are as follows: A Naïve Bayes scheme is implemented and result clearly shows the high accuracy. The Machine learningapproach

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Table 1 Sample Heart disease data set (14 attributes)

Attributes A_i						
Age	Sex	Chest pain	trestbpss: (in mm)	Chol:in mg/dl	Fbs	restecg:
67.0	1.0	4.0	120.0	229.0	0.0	2.0
37.0	1.0	3.0	130.0	250.0	0.0	0.0
41.0	0.0	2.0	130.0	204.0	0.0	2.0
56.0	1.0	2.0	120.0	236.0	0.0	0.0
62.0	0.0	4.0	140.0	268.0	0.0	2.0

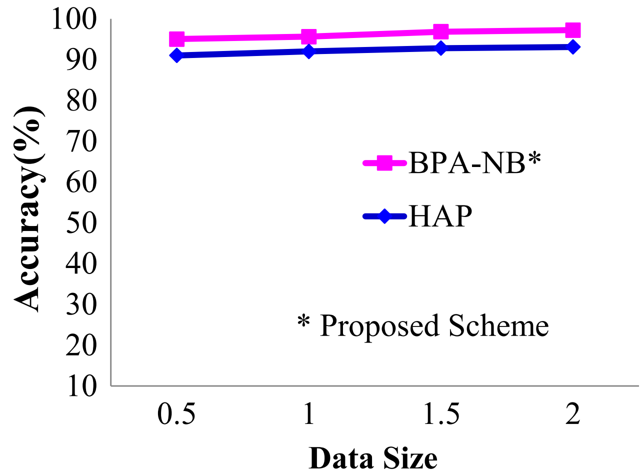

Fig. 1 Accuracy.

(Naïve Bayes) is integrated with spark environment and shown to be a viable predicting solution when dealing with health parameters. The proposed BPA-NB scheme involved twophases including clustering and prediction phase. The clustering phase involves cleaning the obtained data and group the data based on the diseases. The prediction phase finds theclass labels include Yes_p and No_p using Naïve Bayes technique. As a new finding, we developed a Big Data Predictive Analytics Model for Disease Prediction using Machine learning Technique to predict the future status of the patients. We assess the performance of the proposed BPA-NB scheme. The rest of the paper includes five sections. Section 2 presented literature of related works. Section 3 illustratesthe proposed BPA-NB scheme in which build the training model with data. Section 4 reveals thesimulationresults and performance analysis of the proposed BPA-NB scheme in terms of execution time and classification metrics. Finally, Sect. 5 discusses the conclusions and future direction.

Related Works

Prasan Kumar et.al [5] proposed the probabilistic data collection mechanism. It performed correlation analysis of collected data. Finally, a stochastic prediction model is designed to foresee the future health condition of the most correlated patients based on their current health status. Bandwidth utilization of this approach reduces the analysis time. **Sudha Ram et.al** [6] proposed a new technique that used multiple data sources for predicting the number of asthma-related emergency department visits. This system used Twitter data and environmental sensor to predict the number of asthma emergency department visits. **DequanChen**et.al [7] proposed Mayo Clinic healthcaresystem to acquire and store enterprise data. It performs analytics on clinical data for diagnosis, treatment, prevention, or clinical reporting and nonclinical data for scientific research health informatics. **Alexandra**et.,al [8] discussed the challenges associated with machine learning approaches in Big Data platform. Finally, they concluded that the machine learning techniques are best suitable for identifiedchallenges in the era of Big data analytics. **Min chenet et al.,** [9] proposed a CNN-based multimodal disease risk prediction algorithm for healthcare data. It performs

Table 2 Sample Heart disease data set (14 attributes)

Attributes A_i						
thalach:	exang:	oldpeak:	slope:	ca:	thal:	num:
129.0	1.0	2.6	2.0	2.0	7.0	1
187.0	0.0	3.5	3.0	0.0	3.0	0
172.0	0.0	1.4	1.0	0.0	3.0	0
178.0	0.0	0.8	1.0	0.0	3.0	0
160.0	0.0	3.6	3.0	2.0	3.0	3

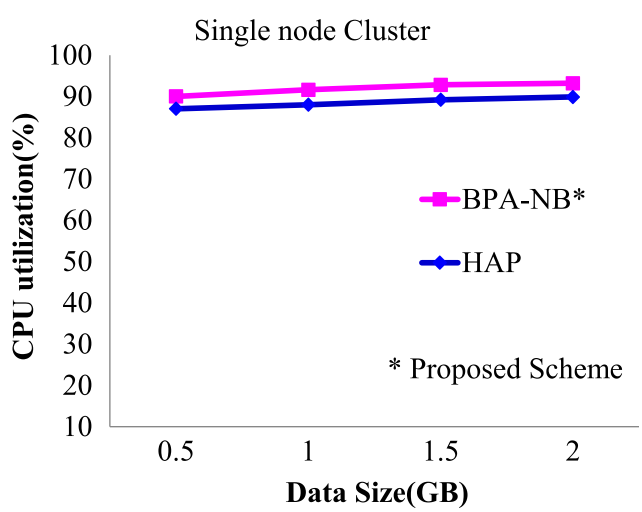

Fig. 2 CPU utilization in Single node cluster

medical data analysis for disease detection in healthcare community. **AbdulsalamYassine** et al., [10] proposed a model that utilizes smart home big data as a means of learning and discovering human activity patterns for health care applications. They propose the use of frequent pattern mining, cluster analysis, and prediction to measure and analyze energy usage changes sparked by occupants' behavior. **Yichuan Wang etal.,** [11] developed a big data analytics framework for healthcare sectors that identified five big data analytics capabilities such as analytical for patterns, unstructured data analytical, decision support, predictive, and traceability. **Gao Zhuetal.,** [12] proposed a novel cluster model such as structured output support vector machine to provide classification for object tracking. The authors are suggested that a set of clustering algorithms performing well for big data. **Daniele Ravetal.,** [13] proposedon applications of deep learning in the fields of bioinformatics, pervasive computing and sensing, medical data and public health. **MohitDayaland**etal., [14] analyzed the health care dataset against different research queries using actionable data. They performeddata analytics using specialized Big data analytics tools. **L. Yang** et al., [15] proposed feature sets for twophase biomedical named entity recognition using semi-CRFs. They used Support vector machine (SVM) in various text processing tasks including named entity recognition. **Wittekand Daranyi** [16] proposed MapReduce-based text mining workflow foreffective use of shared memory and optimized coalesced memory access. Nishitand Anil [15] suggested big data analytics in healthcare. **Marco Viceconti** etal., [16] proposed effective solution for silico medicine that extract by analytical data to build automatic models for individual patients in healthcare. **Javier Andreu-Perez**et.al [17] proposed the new testing hypotheses about disease management from diagnosis to prevention for personalized treatment using characteristics of big data. Health data such as imaging informatics, Health informatics,sensor informatics,and translational bioinformatics providepersonalized information from a diverse data sources.

H. Tamano et al., [18] proposeda programming model for large-scale analysis in hadoop ecosystem. They suggested deep learningmethod to make prediction. It takes advantage of the parallel processing capabilities of a cluster in order to quickly process very large datasets in a fault-tolerant and scalable manner. **Jui-FengYeh** et al., [19] proposed the conditional random fields that used statistical word and parts of speech to detect the grammatical errors. It gave good performance in terms of precision and recall rate. **IndranilPalit** et al., [20] proposedtwo parallel boosting algorithmstocreate a boosted ensemble classifier. This approach allows for protecting privacy data in distributed computing environments. This works well in prediction accuracy and speedup performance metrics. It is not perform well in classification accuracy in random stratification. Also, it has more boosting iterations during scaleup mechanism. **Prasan et al.,** [21] designed a probabilistic data collection model to predict the future health condition of the patients. Machine learning techniques such as Markov model [22], Support vector machine [23], Artificial Bee Colony [24], genetic algorithm [25] and Hybridized neural network [26] are applied for clustering, classification, prediction in healthcare domain and real time monitoring the healthcare environment [30, 32]. Game theory model [27–29] play the vital role in medical application to provide security. Clearly, it is evident from the recent related works shows that there is no existing solution to predict the heart diseases based on the health status. In this paper, we used Naive Bayes machine learning Technique to predict the heart failure that provide high accuracy. Naive Bayesian classifiers employ the probability mechanism that read the data with assumptions for features that make to provide accurate results for prediction.

Proposed Work

The proposed BPA-NB scheme predicts class of heart test data set. We considered two classes such as Yes-P, No-P. The proposed BPA-NB scheme used clustering and statistical classification scheme to form a group and predict a disease. Data sets are collected from UCI machine learning repository. Naive Bayes algorithm was used to build the training model with data. Table 1 and Table 2 show the sample Heart disease data set. The attributes used are as follows

1. Age in years
2. Sex (1 = male,0 = female)
3. Chestpain(1 = typical angina,2 = atypical angina,3 = non angina,4 = asymptomatic)
4. trestbpss: resting blood pressure (in mm Hg on admission to the hospital)
5. chol: serum cholestoral in mg/dl
6. fbs: (fasting blood sugar >120 mg/dl) (1 = true; 0 = false)
7. restecg: resting electrocardiographic results
8. thalach: maximum heart rate achieved
9. exang: exercise induced angina (1 = yes; 0 = no)
10. oldpeak: ST depression induced by exercise relative to rest
11. slope: the slope of the peak exercise ST segment
12. ca: number of major vessels (0–3) colored by flourosopy
13. thal: 3 = normal; 6 = fixed defect; 7 = reversabledefec
14. num: diagnosis of heart disease (angiographic disease status)

The patients within the same department are clustered based on their resemblance. The number of data blocks are generated and distributed among the active servers and all the statistical analysis are performed on those data blocks. The collected data are represented in an intra-cluster matrix ┌*akd*(*ws*). The algorithm 1 describes the cluster formation.

Algorithm 1:

Input: *s* :The size of each individual data partition.

Output: ┌ $akd(ws)$:Intra-cluster correlation factor within window *w*.

$cpd(ws)$: Newly classified patient set within window *w*.

Initialize thd(ws) = 0;

Tp = p in + pban;// Total # of patients and BANs within the department *d*.

for i= 1 **to T_p do**

for j= 1 **to hpdo**

thd$(ws)$is calculated based on Eq. (5);

end for

end for

db = thd/s

Repeat step from 10 to 17 on dbnumber of data blocks;

while(i= 0)|db|

while j= 0 **to hp**

Intra-cluster matrix$Iakd(ws)$[i][j] = $[P\iota k, hpjk]$;

end for

Find the column mean $\rho a\iota k(ws)$ based on the Eq. (14);

end for

Evaluate the variance $(\sigma akd(ws))$ based on Eq. (15);

Calculate standard deviation $(SDkd(ws))$ based on Eq. (16);

Find Intra-cluster correlation (┌$akd(ws)$) based on Eq.(17);

if ┌ akd(ws) ≥ γathen

cp$d(ws)$ = $\{P\iota\}$;

end if

Return ┌wa(ws)andcp$d(ws)$;

Naive Bayes Classification Algorithm

Naive Bayes classification is based on Bayes theorem with an assumption of independence between features. The Bayesian classifier used statistical analysis to predict a future attribute also it is suitable for large datasets. The algorithm 2 shows the naïve Bayes classification to predict the future health status of the clusters. Bayes theorem provides a way of calculating posterior probability P(c|x) from P(c), P(x) and P(x|c).

$$p\left(\frac{c}{x}\right) = p\left(\frac{x}{c}\right)p(c)/p(x) \quad (1)$$

where,

P(c|x)	is the posterior probability of class (c, target) given predictor (x, A_i), where $A_i = \{A_1, A_2, \ldots A_{14}\}$
P(c)	is the prior probability of class p(yes/no)
P(x|c)	is the likelihood which is the probability of predictor given class.
P(x)	is the prior probability of predictor.

Algorithm 2:

Begin

Initialize the dataset (training 60 %, testing 40%)

Calculate diagnosis = "yes", diagnosis = "no" P_{yes}, P_{no} from training input

For each test input samples

For each A_i

Calculate of category of feature based on categorical.

Division

Find p(diagnosis) = "yes", p(diagnosis) = "no" corresponds to that category P(A_i, yes), P(A_i, no) from training input

For each A_n

Predict result_yes = P(A_i, yes), result_no = P(A_i, no);

Calculate the result_yes = result_yes *P_{yes}, result_no = result_no*P_{no};

If (result_yes > result_no) then diagnosis = "yes", else diagnosis = "no".

Where,P_{yes}= Total number of yes/Total number of instances;

P(A_i, yes) = Total number of yes in corresponding category/Total number of yes;

P(A_i, no) = Total number of no in corresponding category/Total number of no;

End

Results and Discussions

Accuracy

The proposed BPA-NBscheme provides higher accuracy than existing system. The proposed BPA-NBscheme initialize and split the dataset to training (60%) and testing dataset (40%). The proposed BPA-NBscheme used the feature of Spark execution environment and its **in-memory clustercomputing** [31]. The proposed system maintains the accuracy above 97% while increasing data size as shown in the Fig. 1. The proposed BPA-NBscheme used Naive Bayes classification algorithm to predict the future status of the health using health parameters. The proposed Machine learning approach learns quickly using normalization that reduces the mean absolute error. Hence, the BPA-NBscheme achieves high accuracy and predicted the results.

CPU Utilization

Figure 2 shows the CPU utilization of single node cluster with varying data size. thatThe proposed system has effectively used the CPU to process the data than the existing system.

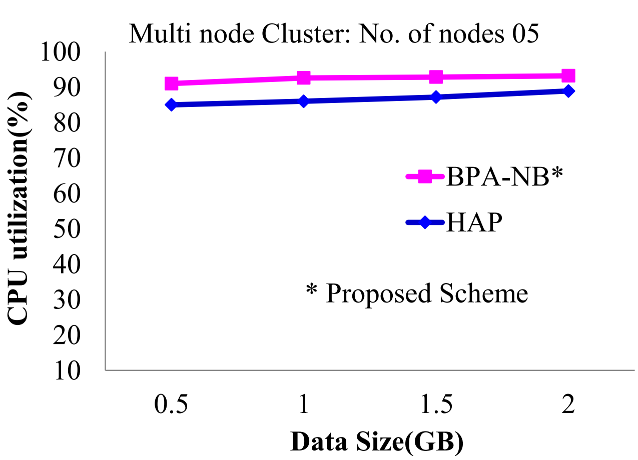

Fig. 3 CPU utilization in Multi node cluster with 05 nodes

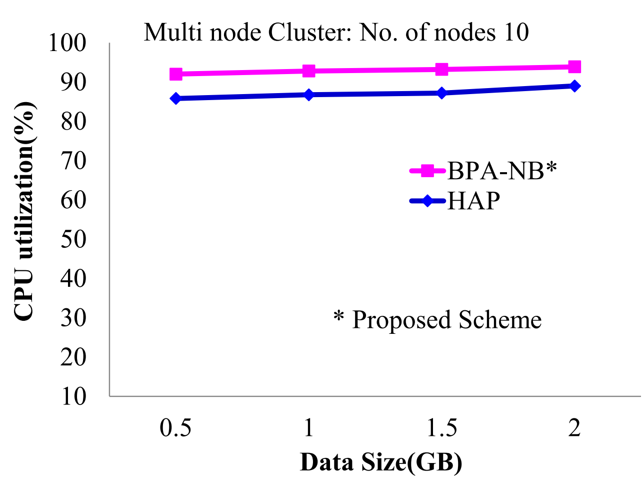

Fig. 4 CPU utilization in Multi node cluster with 10 nodes

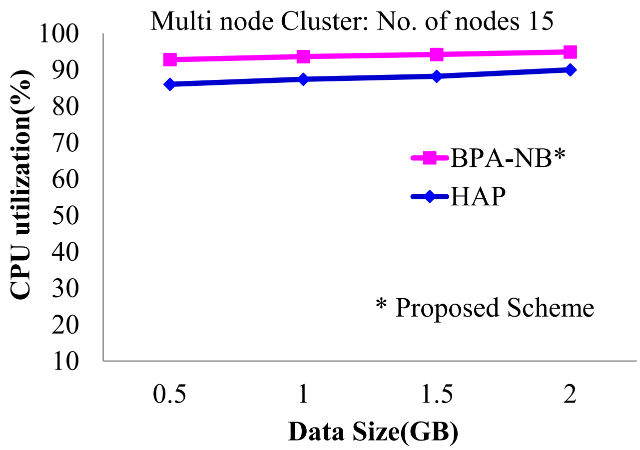

Fig. 5 CPU utilization in Multi node cluster with 15 nodes

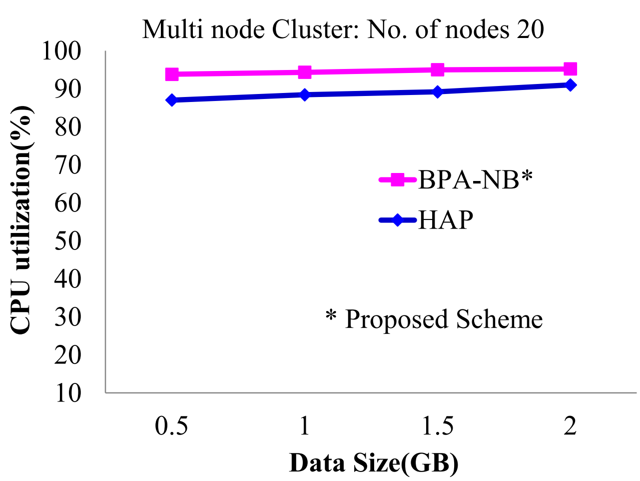

Fig. 6 CPU utilization in Multi node cluster with 20 nodes

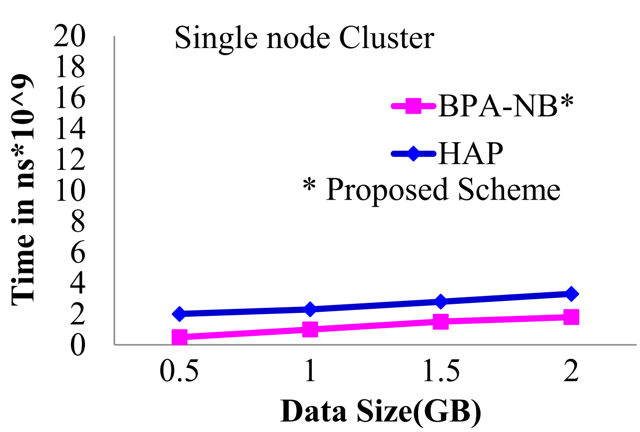

Fig. 7 Processing time in single node cluster

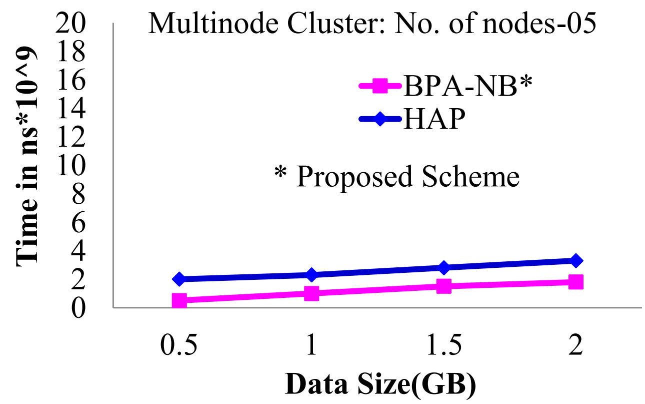

Fig. 8 Processing time in multimode cluster with 5 nodes

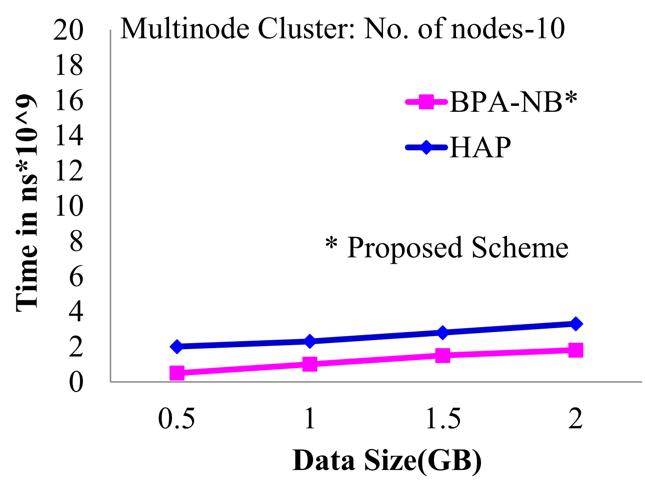

Fig. 9 Processing time in multimode cluster with 10 nodes

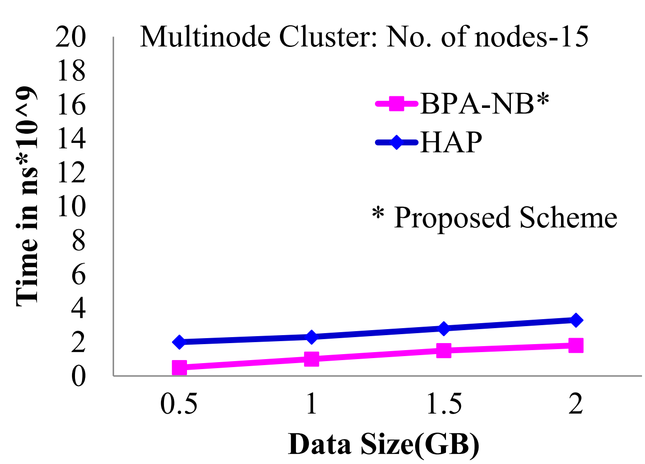

Fig. 10 Processing time in multimode cluster with 15 nodes

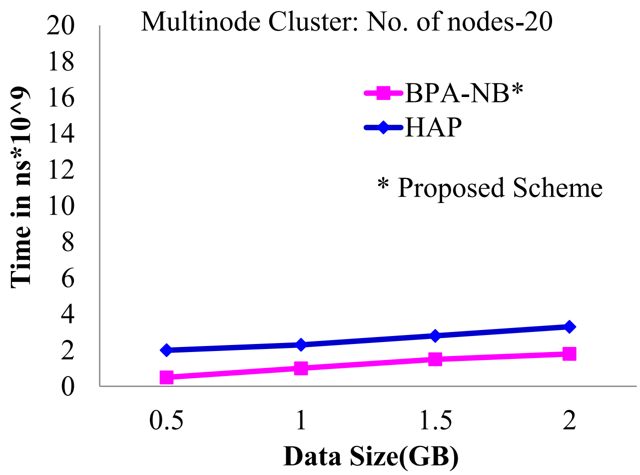

Fig. 11 Processing time in multimode cluster with 20 nodes

This is because analysis performed by Naive Bayes Technique, The CPU utilization of proposed system is more than existing system becausethe proposed system makes use of parallelism to process data. The proposed BPA-NB scheme achieved highCPU utilization than existing scheme. Figure 3, Fig. 4, Fig. 5 and Fig. 6 shows the CPU utilization with multimode clusters by varying nodes 5, 10, 15 and 20 respectively. The proposed system used required maximum CPU for processing the healthcare data because the data was distributed in multi node cluster and executed in parallel.

Processing Time

Fig. 7 shows the processing time ofCPU or process time in single node cluster. It refers the amountof time for which a CPU was used for processing data of a cluster node. The CPU time is measured in nano-seconds. The processing time is faster than the existing system. Figure 8, Fig. 9, Fig. 10 and Fig. 11 shows the processing time with multi-node clusters by varying nodes 5, 10, 15 and 20 respectively. The proposed BPA-NB scheme takes less time to process the varying size of healthcare data. The proposed BPA-NB scheme designed in Hadoop-spark environment to handle the big data. Also, the proposed BPA-NB scheme used map-reduce Naive Bayes algorithm to process varying data in multi-node cluster in parallel manner. It reveals that the proposed scheme used processing time effectively to handle the healthcare data.

Classification report and confusion matrix

Table 4 and Table 5 shows the classification report for training data and test data respectively. Confusion matrix for training data of heart disease specifies the good accuracy of the proposed prediction. The proposed scheme provides better results in terms of precision, recall, F1-score and support for both training and test data.

Confusion Matrix for Training Data

[[2094 145]
[319 85]]

Classification Report for Training Data

Table 4 Classification Report for Trained Data

	Precision	recall	F1-score	support
0	0.87	0.95	0.90	2240
1	0.37	0.21	0.27	404
Avg/total	0.79	0.83	0.80	2644

Confusion Matrix For test Data

[[901 62]
[138 32]]

Classification Report For test Data

Table 5 Classification Report for Test Data

	Precision	recall	F1-score	support
0	0.88	0.93	0.91	964
1	0.35	0.20	0.25	172
Avg/total	0.80	0.82	0.81	1132

Conclusion & Future Work

We have presented a Naive Bayes approach for constructing classifier model to predict the future health condition of heart disease data. The proposed system used probabilistic classification based on Bayes' theorem to analysis the data. The clustering technique is pioneered in the proposed work to filter the unnecessary data and make prediction in effective manner. We designed a map reduce algorithm for Naive Bayes technique that integrated with Apache Spark framework for performing big data predictive analytics that helps to reduce the computation complexity because of its parallelism. The proposed BPA-NB scheme classify and predict the future status from the heart disease data set effectively that discussed in result and discussion section. Finally, the simulation was carried out on the data set from UCI machine learning repository and the results in future prediction ensured that the proposed system improved significantly in terms of accuracy, CPU utilization, and processing time. Future work may be investigate in heterogeneous environment.

References

1. Banu, N. K. S., Swamy, S., Prediction of heart disease at early stage using data mining and big data analytics: A survey, International Conference on Electrical, Electronics, Communication, Computer and Optimization Techniques , IEEE, Mysuru, India, 2016.
2. Wang, L., and Alexander, C. A., Big Data in Medical Applications and Health Care. Current Research in Medicine 6:1–8, 2015.
3. Palit, I., and Reddy, C. K., Scalable and Parallel Boosting with MapReduce. Ieee Transactions on Knowledge And Data Engineering 24(10):1904–1916, 2012.
4. Kumar, P., Mohapatra, S. K., and Shih-Lin, W., Analyzing Healthcare Big Data With Prediction for Future Health Condition. IEEE Access 4:9786–9799, 2016.
5. Alexander, C. A., and Wang, L., Big Data Analytics in Heart Attack Prediction. Journal of Nursing and Care 6(2):1–9, 2017.
6. Ram, S., Zhang, W., and Williams, M., Predicting Asthma-Related Emergency Department Visits Using Big Data. IEEE Journal 19(4): 1216–1223, 2015.
7. Chen, D., Chen, Y., Brownlow, B. N., and Kanjamala, P. P., Real-Time Daily Healthcare Data Into HDFS and Elastic Search Index Inside a Big Data Platform. IEEE Transaction 13(2):595–606, 2017.
8. Heureuxi, A. L., Grolingeri, K., Elyamany, H. F., and Miriama, Machine Learning With Big Data:Challenge and Approaces. IEEE Access 5:7776–7797, 2017.
9. chen, M., Hao, Y., and Hwang, K., Disease Prediction by Machine Learning Over Big Data from Healthcare Communities. IEEE Access 5:8869–8879, 2017.
10. Abdulsalamyassine, S., Mining Human Activity Patterns From Smart Home Big Data for Health Care Applications. IEEE Access 5:13131–13149, 2017.
11. Wang, Y., and Kung, L. A., Terry Anthony Byrd, "Understanding itscapabilities and potential benefits for healthcare organizations". Journal of Technological Forecasting and Social Change 126:3–13, 2018.
12. Gao Zhu, F., A Survey of Clustering Algorithms for Big Data: Taxonomy and Empirical Analysis. IEEE TransactionsEmerging Topics in Computing 2(3):267–279, 2014.
13. Rav, D., Wong, C., and Deligianni, F., Deep Learning for Health Informatics. IEEE Journal of Biomedical and Health Informatics 21(1):4–22, 2017.
14. Dayal, M., and Singh, N., Indian Health Care Analysis using Big Data Programming Tool. Procedia Computer Science 89:521–527, 2016.
15. Yang, L., and Zhou, Y., Exploring feature sets for two-phase biomedical named entity recognition using semi-CRFs. Journal of Knowledge and Information Systems 40(2):439–453, 2014.
16. Wittek, P., and Daranyi, S., Accelerating text mining workloads in a mapreduce-based distributed GPU environment. Journal of Parallel and Distributed Computing 73(2):198–206, 2013.
17. Mehta, N., and Pandit, A., Concurrence of big data analytics and healthcare: A systematic review. International Journal of Medical Informatics 114:57–65, 2018.
18. Viceconti, M., Hunter, P., and Hose, R., Big Data, Big Knowledge: Big Data for Personalized Healthcare. IEEE Journal of Biomedical and Health Informatics 19:4–33, 2015.
19. Andreu-Perez, J., Poon, C. C. Y., Merrifield, R. D., Wong, S. T. C., Yang, G-Z, Fellow, "Big Data for Health", IEEE Journal of Biomedical and Health Informatics, Vol.16, Pp.16–35, 2015
20. Tamano, S. N., and Araki, T., Optimizing multiple machine learning jobs on MapReduce, IEEE International Conference on Big Data Intelligence and Computing and Cyber Science and Technology, Vol.30, pp.59–66
21. Yeh, J-F, Yeh, C-K, Yu, K-H, Li, Y-T, Tsai, W-L, Condition Random Fields-based Grammatical Error Detection for Chinese as Second Language, Department of Computer Science and Information Engineering (2014), Vol. 186, Pp. 537–566
22. Vimal, S., Kalaivani, L., Kaliappan, M., Suresh, A., Gao, X.-Z., and Varatharajan, R., Development of secured data transmission using machine learning based discrete time partial observed markov model and energy optimization in Cognitive radio networks. Neural Comput & Applic, 2018. https://doi.org/10.1007/s00521-018-3788-3.
23. Kannan, N., Sivasubramanian, S., Kaliappan, M., Vimal, S., and Suresh, A., Predictive big data analytic on demonetization data using support vector machine. Cluster Comput, 2018. https://doi.org/10.1007/s10586-018-2384-8 March 2018.
24. SudhakarIlango, S., Vimal, S., Kaliappan, M., and Subbulakshmi, P., Optimization using Artificial Bee Colony based clustering approach for big data. Cluster Computing. https://doi.org/10.1007/s10586-017-1571-3.
25. Kaliappan, M., Augustine, S., and Paramasivan, B., Enhancing energy efficiency and load balancing in mobile adhoc network using dynamic genetic algorithms. Journal of Network and Computer Applications 73:35–43, 2016.
26. Suresh, A., Udendhran, R., and Balamurgan, M., Hybridized neural network and decision tree based classifier for prognostic decision making in breast cancers. Soft Computing, 2019. https://doi.org/10.1007/s00500-019-04066-4.
27. Suresh, A., Udendhran, R., and Balamurgan, M., A Novel Internet of Things Framework Integrated with Real Time Monitoring for Intelligent Healthcare Environment. Journal of Medical System 43(6):165, 2019. https://doi.org/10.1007/s10916-019-1302-9.
28. Suresh, A., Kumar, R., and Varatharajan, R., Health Care Data Analysis using Evolutionary Algorithm. Journal of Supercomputing, 2018. https://doi.org/10.1007/s11227-018-2302-0.
29. Kaliappan, M., and Paramasivan, B., Enhancing secure routing in Mobile Ad Hoc Networks using a Dynamic Bayesian Signalling Game model. Journal of Computers & Electrical Engineering 41: 301–313, 2015.
30. Paramasivan, B., Viju, M. J., Kaliappan, P. M., Development of a Secure Routing Protocol using Game Theory Model in Mobile Ad Hoc Networks, Journal of Communications and Networks, 17, 1, 2015
31. Vimal, S., Kalaivani, L., and Kaliappan, M., Collaborative approach on mitigating spectrum sensing data hijack attack and dynamic spectrum allocation based on CASG modeling in wireless cognitive radio networks. Cluster Computing, 2017. https://doi.org/10.1007/s10586-017-1092-0.
32. Mariappan, E., Kaliappan, M., Vimal, S., Energy Efficient Routing protocol using Grover's Searching algorithm using MANET, Asian Journal of Information Technology,Vol:15, no.24,2016

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