

Examination of Healthcare Diagnosis using Iot

Suguna M, Prakash D, Cynthia. J

Abstract: In recent years, online applications, spare many services for wellness of health related issues. The application is kept updated so that the health related data are kept modernized for future references. The application collects information from IoT devices and then compares them with other existing data from the prevailing records with the same disease. The collected data is then reserved in a database that hold all records about the healthcare issues. Cloud computing technology is used to guard and reserve the healthcare records. Cloud and IoT technology are connected to provide users with a completely developed healthcare record. The existing system makes use of Fuzzy Rule Based Neural Classifier that helps in assembling and categorizing the diabetes data under the guidance of severity analyzer. This work, present the comparison of some classification algorithms and obtain the accuracy, the dataset collected is a real-time dataset. The output and results are tabulated after the comparison of the algorithms.

Keywords : Cloud, IOT, k-Start, Naive Bayes, healthcare.

I. INTRODUCTION

The forthcoming technology will be flapping beyond the thoughts of humans and ahead of the long-established technology. IoT is the recently developing technology that uses IoT devices. The greatest advantage provided by Cloud computing is the end-to-end service for the condemned accessing of the applications from anywhere around the world. The developing application that uses IoT technology is the healthcare. The utmost seriousness for a patient is the security and assurance about their health records.

The information accumulated from the patients using devices are stacked away in a database. The safety for such preserved, confidential data from unaccredited users is not easy to solve. IoT and Cloud computing are capable of bonding easily and collaboratively dependent on each other. Both together provide a well-developed platform for collecting patient data every second and share them with the respective doctors attending them.

II. RELATED WORKS

The classification algorithm Fuzzy Rule Based Neural Classifier has shown better results than the existing algorithm. This algorithm was suggested for identifying the severity of any kind of disease [1]. The proposed idea has set forth a new healthcare application for utility functions. The skeleton of this application based on u-healthcare services [5]. Due to, increasing range of sick, elderly and disabled people, their

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* Correspondence Author

Dr. Suguna M, Assistant Professor-II, CSE Department, Kumaraguru College of Technology, Coimbatore, Tamilnadu, India

Dr. Prakash D, Associate professor, Department of EEE, Vel Tech Muti Tech Dr. Rangarajan Dr. Sakunthala Engineering College, Chennai, Tamilnadu, India

Dr. Cynthia. J, Professor, CSE Department, Kumaraguru College of Technology, Coimbatore, Tamilnadu, India.

health records are required to be stored as made available to professionals for references [11].

III. ORGANIZATION MODEL

The dataset collected from the real-time is first collected and subjected to data accumulated, the data accumulated has been getting after cleaning, integrated. The missing values are filled and noisy values are removed finally the data's are filtered.

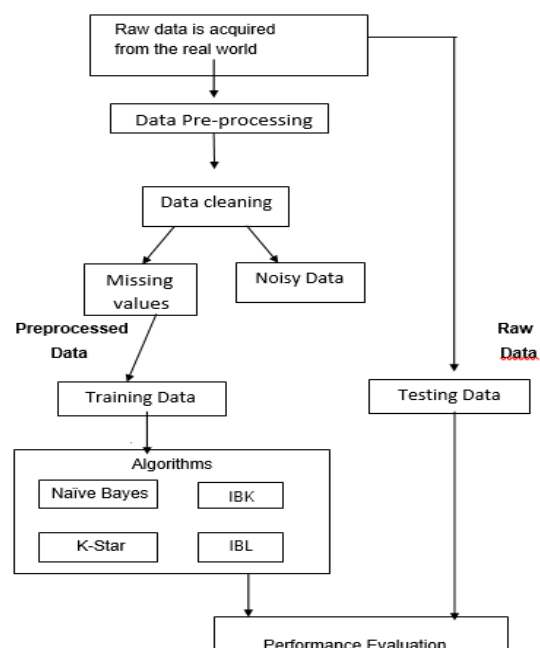


Figure 1: Architecture diagram of the proposed system

The algorithms are executed with the pre-processed and accumulated data and the result summary is tabulated with accuracy, percision and recall values obtained from the output. The disease severity is analysed and the treatment to be taken is done based the data collected which in turn is compared with the existing data to calculate the crucial stage value.

IV. IMPLEMENTATION AND RESULTS

In this simulation, results for various modules, namely, data pre-processing, classification using Naive Bayes, IBK and K-star are derived. The benefits of the classification system are employed to find the classification accuracy and processing time on multiple features. The prediction model employed in the output probability of defect proneness for each module for which a testing is completed. To classify module as defective, one can use a minimum threshold and minimum support set by the user and different choices of thresholds will give varying rates of false positives and false negatives



4.1 Data preprocessing

Data preprocessing prepares raw data for further processing involved cleaning, consolidation, transformation, reduction and discretization. In this phase, the coronary artery heart disease dataset before and after preprocessing all types of noisy irrelevant data are removed and missing values are filled.

4.2 Naive Bayes Algorithm

Applying naive Bayes algorithm to the training set for both the datasets and finally the results are tabulated. Table 1 explains the confusion matrix, accuracy and timely processing of the coronary artery disease dataset.

Table 1: Confusion matrix of coronary artery disease

A	B	C	
Percutaneous coronary intervention	Coronary artery bypass grafting	Percutaneous coronary revascularization	
26	10	5	A
11	22	7	B
2	7	9	C

The following figure 2 describes the summary of the trained model gets tested using testing data to find whether it is defective or non-defective for naive Bayes algorithm.

Correctly Classified Instances	57	57.5758 %
Incorrectly Classified Instances	42	42.4242 %
Kappa statistic	0.3362	
Mean absolute error	0.3655	
Root mean squared error	0.4303	
Relative absolute error	86.5937 %	
Root relative squared error	93.7387 %	
Coverage of cases (0.95 level)	98.9899 %	
Mean rel. region size (0.95 level)	89.5623 %	

Figure 2: Summary of Naïve Bayes related to coronary artery disease

Table 2 shows the accuracy and processing time for Coronary Artery dataset, the percentage split is taken as 30% and trained, the remaining dataset is tested, and the True positive (TP) value obtained is 0.367, False positive (FP) value is 0.343 the accuracy obtained is 36.734% this percentage split has been processed within 0.04 seconds and finally the percentage split that has given high accuracy of 57.57% is 70% with TP rate 0.576 and FP rate 0.236 finally the processing time taken is 0.02 seconds and Table 6.2 shows the accuracy and processing time for Peripheral arterial dataset, the percentage split is taken as 30% and trained, the remaining dataset is tested, and the True positive (TP) value is 0.357, False positive (FP) value is 0.368 the accuracy obtained is 35.66% this percentage split has been processed within 0.10 seconds and finally the percentage split that has given high accuracy of 48.92% is 70% with TP rate 0.485 and FP rate 0.387 finally the processing time taken is 0.02 seconds.

Table-2 The accuracy based on classes for coronary artery disease dataset.

TP Rate	FP Rate	Precision	Recall	Accuracy (F-measure)	Time processing (MCC)
0.634	0.224	0.667	0.634	0.650	0.413
0.550	0.288	0.564	0.550	0.557	0.263
0.500	0.148	0.429	0.500	0.462	0.332

0.576	0.236	0.582	0.576	0.578	0.338 (Weighted Average)
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4.3 IBK Algorithm

Applying IBK algorithm to the training set for the datasets and finally the results are tabulated. Table 3 explains the confusion matrix, accuracy and timely processing of the coronary artery disease dataset.

Table 3: Confusion matrix of coronary artery disease

A	B	C	
38	3	0	A
27	12	1	B
9	0	9	C

The following figure describes the summary of the executed for IBK algorithm,

Correctly Classified Instances	59	59.596 %
Incorrectly Classified Instances	40	40.404 %
Kappa statistic	0.3386	
Mean absolute error	0.3376	
Root mean squared error	0.4109	
Relative absolute error	79.9865 %	
Root relative squared error	89.5048 %	
Coverage of cases (0.95 level)	100 %	
Mean rel. region size (0.95 level)	91.5825 %	

Figure 3: Summary of IBK algorithm related with coronary artery disease

Table 4 the accuracy based on classes for coronary artery disease dataset.

TP Rate	FP Rate	Precision	Recall	Accuracy (F-measure)	Time processing (MCC)
0.927	0.621	0.514	0.927	0.661	0.347
0.300	0.051	0.800	0.300	0.436	0.341
0.500	0.012	0.900	0.500	0.643	0.624
0.596	0.280	0.700	0.596	0.567	0.395 (Weighted Average)

4.4 K-Star Algorithm

Applying K-Star algorithm to the training set for the datasets and finally the results are tabulated. Table 5 explains the confusion matrix, accuracy and timely processing of the coronary artery disease dataset.

Table 5: Confusion matrix of coronary artery disease

A	B	C	
26	13	2	A
14	25	1	B
5	7	6	C

The following figure describes the summary of the executed for K-Star algorithm,

Correctly Classified Instances	57	57.5758 %
Incorrectly Classified Instances	42	42.4242 %
Kappa statistic	0.3063	
Mean absolute error	0.2828	
Root mean squared error	0.5318	
Relative absolute error	67.0003 %	
Root relative squared error	115.8487 %	
Coverage of cases (0.95 level)	57.5758 %	
Mean rel. region size (0.95 level)	33.3333 %	

Figure 4 Summary of K-Star algorithm related with coronary artery disease

Table 6 The accuracy based on classes for coronary artery disease dataset.

TP Rate	FP Rate	Precision	Recall	Accuracy (F-measure)	Time processing (MCC)
0.634	0.328	0.578	0.634	0.605	0.303
0.625	0.339	0.556	0.625	0.588	0.282
0.333	0.037	0.667	0.333	0.444	0.398
0.576	0.279	0.585	0.576	0.569	0.312 (Weighted Average)

4.5 IBL Algorithm

Applying IBL algorithm to the training set for the datasets and finally the results are tabulated. Table 7 explains the confusion matrix, accuracy and timely processing of the coronary artery disease dataset.

Table 7: Confusion matrix of coronary artery disease

A	B	C	
33	6	2	A
2	37	1	B
2	2	14	C

The following figure describes the summary of the executed for IBL algorithm,

Correctly Classified Instances	84	84.8485 %
Incorrectly Classified Instances	15	15.1515 %
Kappa statistic	0.7596	
Mean absolute error	0.1571	
Root mean squared error	0.2803	
Relative absolute error	37.2135 %	
Root relative squared error	61.0504 %	
Coverage of cases (0.95 level)	100 %	
Mean rel. region size (0.95 level)	66.33 %	

Figure 5: Summary of IBL algorithm related with coronary artery disease

Table 8 The accuracy based on classes for coronary artery disease dataset.

TP Rate	FP Rate	Precision	Recall	Accuracy (F-measure)	Time processing (MCC)
0.805	0.069	0.892	0.805	0.846	0.749

0.925	0.136	0.822	0.925	0.871	0.778
0.778	0.037	0.824	0.778	0.800	0.758
0.848	0.090	0.851	0.848	0.848	0.762 (Weighted Average)

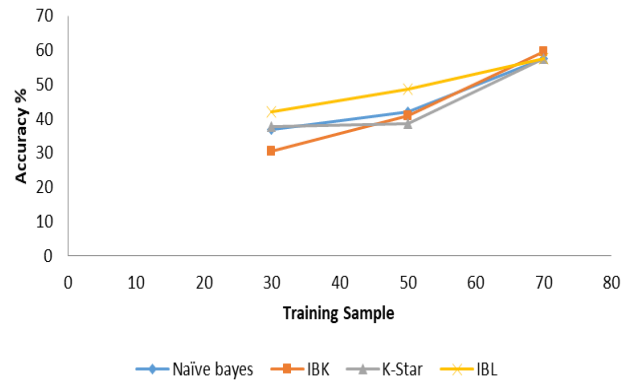


Figure 6. Comparison of the coronary artery disease dataset with accuracy

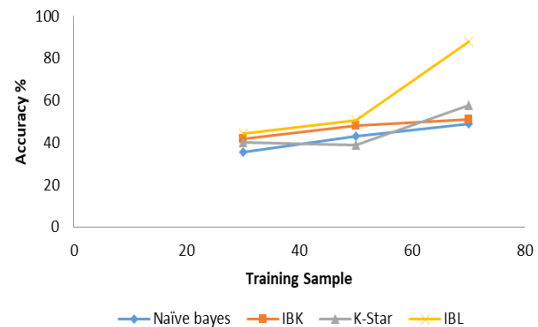


Figure 7. Comparison of the peripheral artery disease dataset with accuracy

The Figure 6 explains the accuracy comparison of the three algorithms Naïve Bayes, IBK, K-Star and IBL for a coronary artery dataset. The percentage split with 70% in IBL algorithm has given the high accuracy of 57.57%. The Figure 7 explains the accuracy comparison of the three algorithms Naïve Bayes, IBK, K-Star and IBL for peripheral arterial dataset has given high accuracy at 70%.

V. CONCLUSION

The recent research proves that the classification algorithms, the IBL algorithm has given the maximum accuracy. It is proved to have given extraordinary accuracy result. The future work is that the collected dataset is stored in cloud database and is stored with high security by providing the doctors with separate user id and password for authenticated logging. This helps to prevent the secured data from getting stolen.



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