Clustering the Age Classified Preprocessed Automated Blood Cell Counter Data using K-Means First Distinct Element Selection and Random Selection Algorithms

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ABSTRACT

The raw Complete Blood Count (CBC) or Full Blood Count (FBC) data from an Automated Blood Cell Counter are collected and transformed in to a Preprocessed and Flattened data using the preprocessing phases of the Knowledge Discovery in Databases. The data is classified into child and adult data sets. The transformed data is used to create clusters of the database in this paper. The K-Means algorithm with two initial mean selection such as first element selection and random element selection is applied on the attributes of the Automated Blood Cell Counter Data to form various clusters. Twelve thousand records are taken from a clinical laboratory for processing.

General Terms

Algorithms.

Keywords

Hematology, Blood Cell Counter, Knowledge Discovery in Databases, Data Mining, Clustering, K-Means Clustering.

1. INTRODUCTION

A huge volume of automated medical data are currently available in various forms such as text, numbers, combination of text and numbers, images, scan reports, video and audio reports. This data are used along with various analysis techniques to generate results that can be used by the health care professionals in efficient decision making.

Hematology is the study of blood, diseases related to blood and blood forming organs such as bone marrow. Clinical Pathology is a study that is concerned with conducting laboratory experiments on body fluids such as blood and urine to diagnose diseases. Hematology department of Clinical Pathology performs various tests on blood. Some of the common tests on blood are the Complete Blood Count (CBC) to diagnose diseases such as anemia and some types of blood cancers, Erythrocyte Sedimentation Rate (ESR) to diagnose inflammation and Prothrombin Time (PT) to diagnose coagulation disorders.

Complete Blood Count (CBC) [1] or Full Blood Count (FBC) of the blood can be found using either a manual procedure or an automated procedure. A Blood Cell Counter [2] is an automated system that generates the CBC blood test results.

The preprocessing phases of the Knowledge Discovery in Databases (KDD) [3,4] is used to convert the raw Automated Blood Cell Counter Data into a form that is appropriate for the Data Mining process and then to generate meaningful results from data. The KDD steps are hence applied in this paper on the blood cell counter data to generate knowledge.

Various combinations of Data Mining classification algorithms are used on medical data for efficient classification of the data. [5] K-Means clustering is used to predict missing attribute values in four types of medical data sets such as Dermatology, Cleveland Heart, Lung Cancer and Wisconsin. [6] Data mining techniques are used to explore physicians' therapeutic decisions when clinical guidelines do not provide recommendations.[7]

Medical data is taken most of the times from medical records [8] and the data is found to be heterogeneous in nature. The privacy issues are to be finalized before handling medical data. [9] The data that is taken from the Blood Cell Counter for our work is De-identified and the patient id and names are changed by the Clinical Pathology department before supplying the medical data for analysis.

The quality of Blood Cell Counter Data is ensured by the application of range checks and delta checks on the various attributes of the data.[10] Association rules are generated for the Automated Blood Cell Counter Data.[11] Automated Blood Cell Counter Data is clustered using the RBC attribute where the initial mean is selected as first k elements from the sorted ABCC data. [12] Genetic Algorithm (GA) and Entropy based fuzzy clustering (EFC) are used to assign k-means initial cluster centers for clustering PIMA Indian diabetic dataset. [13]

2. MATERIALS AND METHODS

2.1 Automated Blood Cell Counter Data

A Blood Cell Counter is an automated machine that can be loaded with blood samples and Complete Blood Count of the given blood samples are generated as an excel report. The report also contains the patient id, hospital number, date and time of the test which are extracted from the barcode pasted on the blood sample container. The number of red blood cells, white blood cells and platelets are some of the blood counts generated by the Automated Blood Cell Counter.

2.2 Data collection

Twelve thousand cell counter data are collected from a Clinical Pathology department of a reputed hospital. The data is present as an excel file.

2.3 Automated Blood Cell Counter Data Format

The Blood Cell Counter Data is given as an excel file. The Blood Cell Counter data consists of values for each sample of blood for the various attributes such as RBC, WBC, PId, SId, PAge, PGender, RDate, RTime, Hgb, MCH and so on. The list of attributes[5] along with a detailed description is shown in table 1. A sample of the data is given in table 2.

Table 1. Automated Blood Cell Counter Data Attributes

Attribute	Attribute Description
PID	Patient Id
R1DATE	Run Date
R1TIME	Run Time
PAGE	Patient Age
PGENDER	Patient Gender
SID	Sample Id
RBC	Red Blood Cell Count
WBC	White Blood Cell Count
Hgb	Hemoglobin Concentration
Hct	Hematocrit
MCV	Mean Cell Volume
MCH	Mean Cell Hemoglobin
MCHC	Mean Cell Hemoglobin
RDW	Red cell Distribution Width
Plt	Platelet Count
Pct	Prothrombin Consumption Time
MPV	Mean Platelet Volume
PDW	Platelet Distribution Width
NE%	Neutrophil percent
LY%	Lymphocyte percent
MO%	Monocyte percent
EO%	Eosinophil percent
BA%	Basophil percent

2.4 Knowledge Discovery in Databases (KDD)

The data is subjected to the KDD processes to generate knowledge from it. The processes include Data Cleaning, Data Integration, Data Selection, Data Transformation, Data Mining, Generation of Patterns and Knowledge Interpretation.

In Data Cleaning the irrelevant data are removed from the collected data. In Data Integration multiple sources are combined into a data warehouse. The Data Selection process is involved with the selection of data relevant to the analysis and extracting them from the integrated data. The selected data is transformed to the appropriate form for the mining procedure.

The process of extracting useful and implicit information from the transformed data is referred to as Data Mining. In Pattern Evaluation interesting patterns are identified from the processed data. The discovered knowledge is visually presented to the user in the Knowledge Representation process.

2.5 Data Mining

Data Mining is the Knowledge Discovery stage of KDD and it is the process of extracting implicit, useful, previously unknown, non-trivial information from data. The techniques involved in Data Mining are grouped as Classification, Clustering, Association Rules and Sequences that represent the knowledge generated from the data.

Classification is a supervised learning process and it maps data into known classes using Decision Trees, Neural Networks and Genetic Algorithms. Clustering is an unsupervised learning and it groups similar data into unknown clusters using K-Means, Nearest Neighbour and various other algorithms. Association Rule Mining (ARM) uncovers relationships among data in a database.

2.6 Classification

Classification is used to classify each item in a set of data into one of the predefined set of classes or groups. Classification techniques use Decision Trees, Neural Networks and so on. Classification algorithms are supervised in nature as they use the class labels.

2.7 Clustering

Clustering is the task of assigning a set of objects into groups so that objects in the same group are more similar to each other than the objects in other groups. Clustering is an unsupervised algorithm and it does not use class labels. The class labels are needed for the Classification algorithms.

Table 2. Sample Automated Blood Cell Counter Data

Patient ID	Gender	Run1 Date	Age	WBC	RBC	Hgb	Hct	MCV	MCH	MCHC	RDW	Plt	Pct	MPV
110324010	Male	01/02/201	30"Years	4.43	4.97	17.2	50.5	101.5	34.64	34.13	13.9	235.	0.18	7.75
110324010	Male	01/02/201	24"Years	15.5	3.38	9.44	28.4	83.84	27.86	33.23	16.2	343.	0.29	8.66
		01/02/201		6.82	4.50	13.9	41.2	91.46	30.99	33.89	13.0	143.	0.20	14.0
110324010	Male	01/02/201	50"Years	4.26	1.96	7	20.1	102.5	35.68	34.81	18.8	93.4	0.07	8.35
110324010	Femal	01/02/201	44"Years	14.2	3.64	11.0	31.9	87.7	30.44	34.72	12.7	272.	0.25	9.39
110324010	Femal	01/02/201	23"Years	16.3	3.84	8.66	27.3	71.22	22.51	31.61	18.9	184.	0.23	12.5
110324010	Male	01/02/201	39"Years	9.48	2.32	7.41	21.4	92.03	31.81	34.56	14.1	92	0.08	9.25
110324010	Male	01/02/201	51"Years	7.99	4.72	14.1	41.7	88.31	29.98	33.95	15.7	87.7	0.07	8.19
110324010	Male	01/02/201	73"Years	15.6	4.09	12.0	36.1	88.35	29.5	33.39	13.8	223.	0.26	11.9
110324011	Male	01/02/201	54"Years	7.79	2.33	6.73	20.1	86.54	28.85	33.33	19.3	187.	0.21	11.5

Some of the major clustering models are Centroid based clustering, Density based clustering, Connectivity based clustering and Distribution based clustering. The K-Means Clustering is a Centroid based clustering model in which the database is partitioned into K clusters in which each record belongs to the cluster with the nearest mean value. The algorithm starts with given initial set of mean values and allocates each object to a cluster with nearest mean value. The mean values for each cluster are calculated then using the elements in each cluster. The K-Means algorithm used for this paper is shown in figure 1.

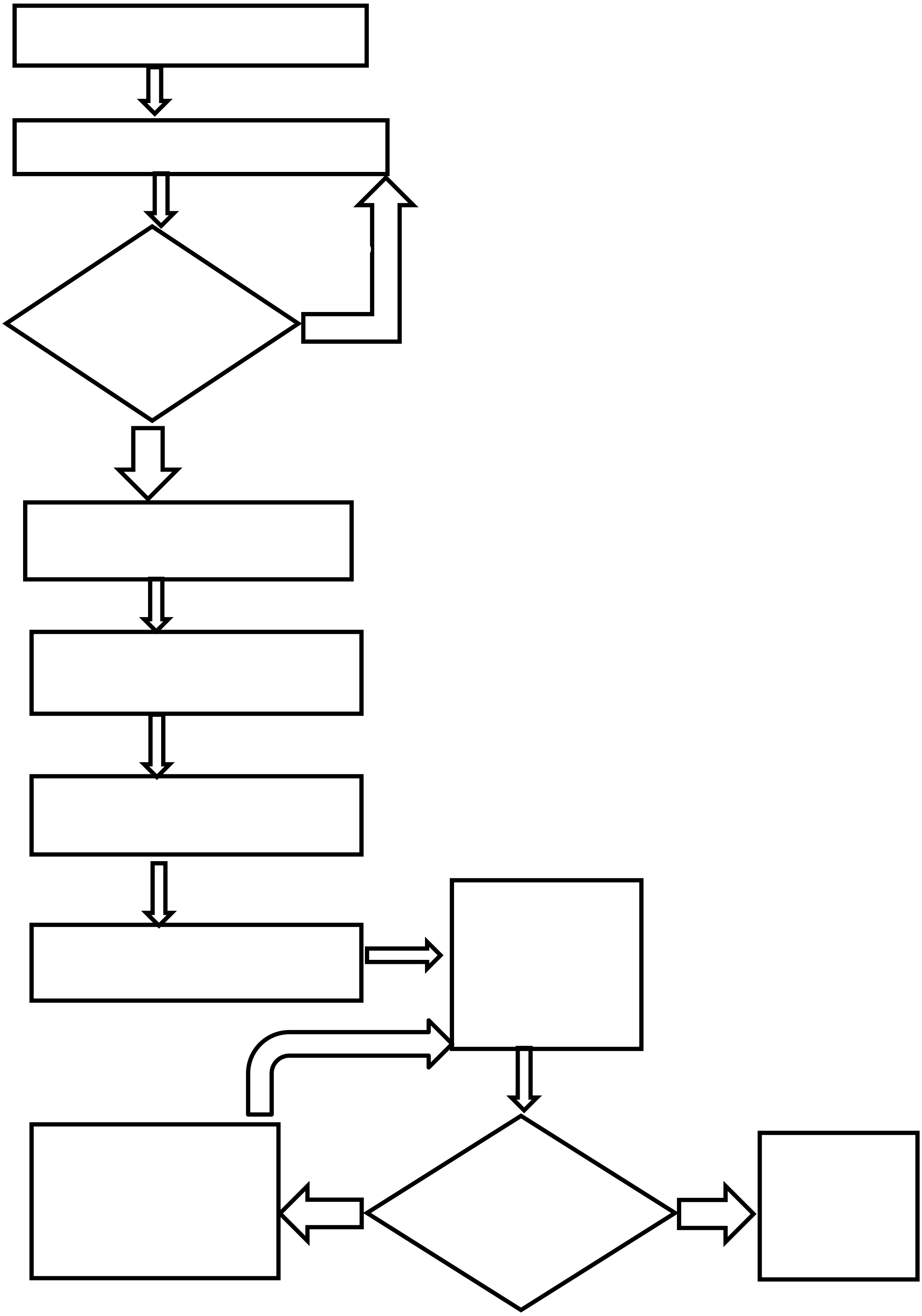


Figure 1 K-Means Algorithm used

The ABCC Data are clustered using two initial mean selection techniques such as First K distinct elements selection and K Random elements selection. The interface for the application is shown in figure 2.

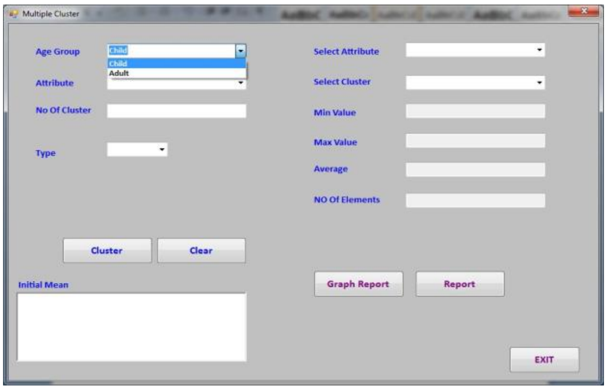


Figure 2 application Interface

3. RESULTS AND DISCUSSION

The Cell Counter Data was taken as a raw data and the preprocessing phase of the KDD process was applied on the data to generate transformed data that was used to extract knowledge from the data.

3.1 Data Cleaning

The process of detecting and correcting or removing corrupt or inaccurate records from a record set, table, or database is Data Cleaning. The missing values in the Blood Cell Counter data cannot be replaced by any other value and hence those records were not considered for further processing.

The attributes RBC, WBC, Hg count, MCH, MCHC, MCV, MPV, PCT, RDW and WBC components percentages were required for analyzing the blood cell counter data and hence the records without these fields were removed. The resultant excel file contained the records with patient id, gender, age, date and time of results and the blood count fields were selected for further processing.

3.2 Data Selection

The cleaned blood cell counter data was taken as the data source for data selection process. The attributes Patient Id, Age, RBC, MCV, MCH, MCHC and RDW were selected for the knowledge generation from the ABCC data and a sample of the selected data is shown in table 3.

3.3 Data Transformation

In the Data Transformation stage the data are transformed or consolidated in to forms appropriate for mining. The excel data is converted into a SQL Data base.

3.4 Classification

The entire Automated Blood Cell Counter Data is classified using Decision Tree algorithm into two sets such as Adult and Child based on the age of the patient. If the age of the patient is less than 12, then the record is for a child and otherwise for adult and is shown in figure 3.

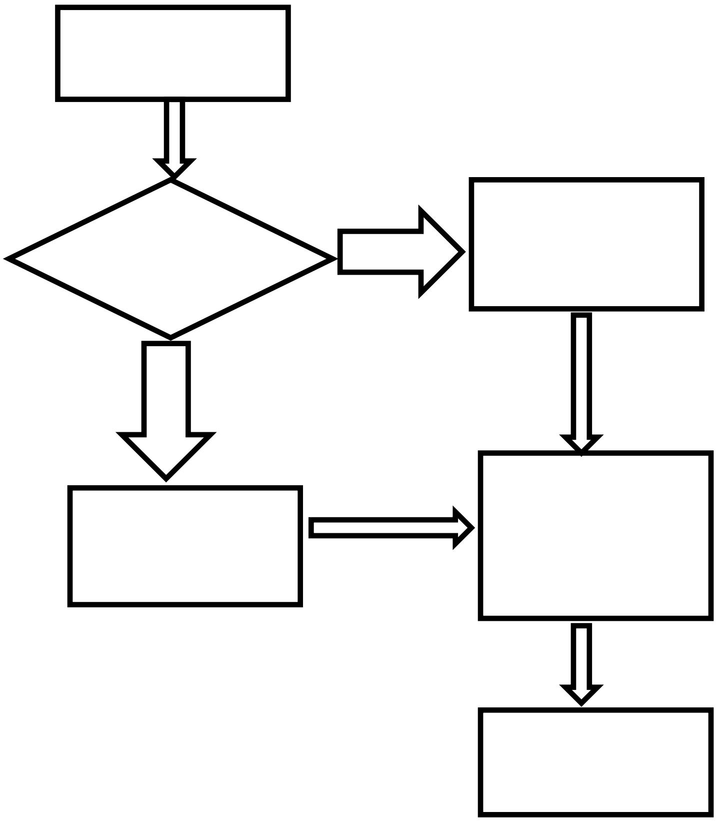


Figure 3 Child, Adult Classification

Table 3 Sample Preprocessed Data

Patient ID	Age	WBC	RBC	Hgb	Hct	MCV	MCH	MCHC	RDW	Plt	Pct	MPV
1103240101	30"Years"	4.43	4.976	17.24	50.51	101.5	34.64	34.13	13.98	235.8	0.182	7.75
1103240102	24"Years"	15.52	3.389	9.44	28.41	83.84	27.86	33.23	16.22	343.2	0.297	8.66
1103240104	50"Years"	4.26	1.961	7	20.1	102.5	35.68	34.81	18.84	93.4	0.078	8.35
1103240105	44"Years"	14.21	3.642	11.09	31.94	87.7	30.44	34.72	12.7	272.8	0.256	9.39
1103240106	23"Years"	16.39	3.845	8.66	27.39	71.22	22.51	31.61	18.92	184.8	0.231	12.54
1103240107	39"Years"	9.48	2.329	7.41	21.43	92.03	31.81	34.56	14.13	92	0.085	9.25
1103240108	51"Years"	7.99	4.729	14.18	41.76	88.31	29.98	33.95	15.73	87.7	0.071	8.19
1103240109	73"Years"	15.65	4.092	12.07	36.15	88.35	29.5	33.39	13.82	223.1	0.266	11.94
1103240111	54"Years"	7.79	2.333	6.73	20.19	86.54	28.85	33.33	19.39	187.6	0.216	11.52

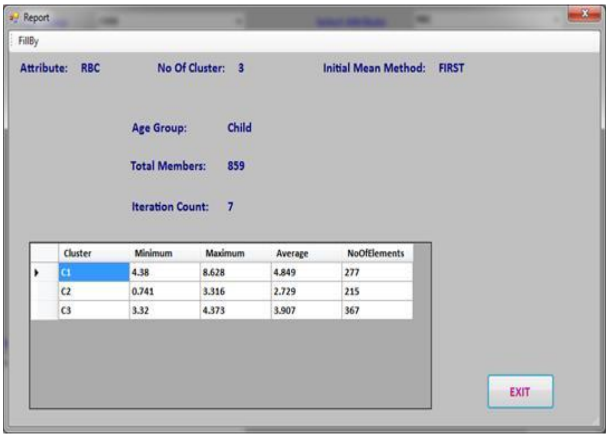
3.5 Clustering

The classified ABCC Adult data and ABCC child data are separately clustered using the attributes of the ABCC Data into K clusters where the K value is given by the user. The attributes RBC, MCV, MCH, MCHC and RDW are used for clustering. The initial mean selections First element selection and Random element selection generates different set of clusters of data.

In the first element selection method the first K elements are taken as the starting mean values and all the elements are compared with the mean values and the records are placed in the cluster in which the element value and the mean value are closer. If there is a tie the element is placed in the first cluster among the set of equal clusters. The final cluster mean values are also generated. In the Random element selection method, K random elements are selected as the starting mean values.

The cluster details such as the minimum element, maximum element, average value of the elements, number of elements per each cluster and the number of iterations for the completion of the clustering process are recorded.

Figure 4 shows the clustering details for the classified Child data for attribute RBC and K = 3 and initial selection of First element selection and figure 5 shows the cluster details for Random element selection.



Attribute: RBC

No Of Cluster: 3

Initial Mean Method: FIRST

Age Group: Child

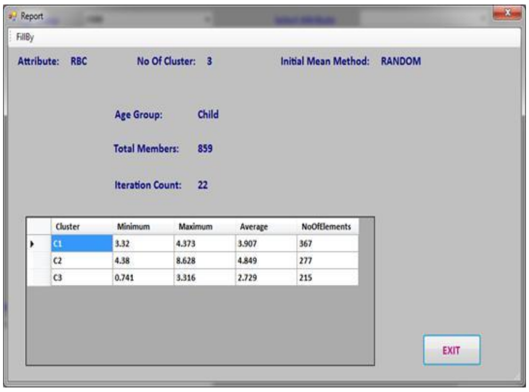
Total Members: 859

Iteration Count: 7

Cluster	Minimum	Maximum	Average	NoOfElements
C1	4.38	8.628	4.849	277
C2	0.741	3.316	2.729	215
C3	3.32	4.373	3.907	367

Figure 4 Clustering for Child K = 3 RBC First Selection

The cluster details such as minimum, maximum and average for child, RBC, K = 3 and for the first element selection and random element selection are shown in a graphical representation in figures 6 and 7.



Attribute: RBC

No Of Cluster: 3

Initial Mean Method: RANDOM

Age Group: Child

Total Members: 859

Iteration Count: 22

Cluster	Minimum	Maximum	Average	NoOfElements
C1	3.32	4.373	3.907	367
C2	4.38	8.628	4.849	277
C3	0.741	3.316	2.729	215

Figure 5 Clustering for Child K=3 RBC Random Selection

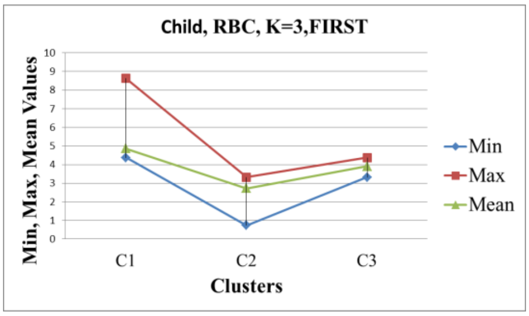


Figure 6 Clustering for Child K = 3 RBC First Selection

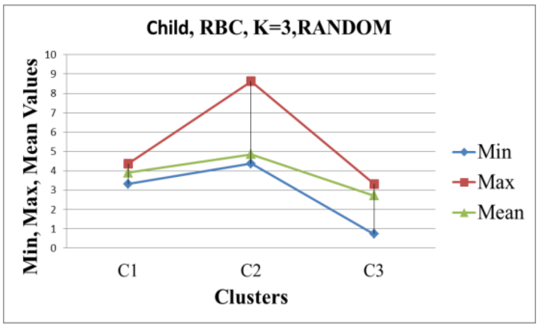


Figure 7 Clustering for Child K=3 RBC Random Selection

The number of iteration required for clustering the Child data and Adult data for the attribute RBC and for the values of K =

3,4,5 and for the First selection and Random selection of initial mean selection are given in table 4.

Table 4 Iteration Table for Child and Adult for RBC K = 3,4,5 and First selection and Random selection

K-Value	Child		Adult	
	First	**Random**	**First**	**Random**
3	7	22	27	11
4	17	16	40	21
5	23	10	64	76

The results show that the number of iterations required for clustering child data for RBC using First Selection is better than Random Selection for K = 3 and is equal for K = 4 and is not better for K = 5 whereas the number of iterations required for clustering adult data for RBC using Random Selection is better than First Selection for K = 3 and 4 and is not better for K = 5.

The number of elements in each of the clusters formed using RBC, MCV, MCH, MCHC and RDW when the k value is 3 for First Selection and Random Selection are given in table 5.

The results show that there is not much difference in the performance of clustering by First Selection and Random Selection with respect to the number of elements per cluster.

Table 5 No. of elements K = 3, First selection and Random selection for RBC, MCV, MCH, MCHC and RDW for Adult ABCC Data

Attribute	Initial Mean Selection	Number of Elements		
		Cluster 1	Cluster 2	Cluster 3
RBC	First	3071	2028	1358
	Random	2031	1357	3069
MCV	First	3866	1061	1528
	Random	1061	1528	3866
MCH	First	3431	917	2108
	Random	917	2108	3431
MCHC	First	2585	492	3379
	Random	2585	492	3379
RDW	First	332	4557	1566
	Random	1566	332	4557

4. CONCLUSION

A brief study of Hematology, Automated Blood Cell Counter and Blood Cell Counter data is presented in the paper. The format of the blood cell counter result was described and few of the attributes were selected for processing, based on the knowledge given by the Clinical Pathologist. The KDD steps were explained and were applied on the Blood Cell Counter Data to convert the raw data into a transformed data and clusters are formed using two initial mean selection such as first selection and random selection. The performances of the two selection methods are compared.

A single test result was considered here and the data is to be collected from various laboratories and various Blood Cell Counter machines for integrating the data.

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6. REFERENCES

[1] Complete Blood Count (CBC) with Five-Part Differential NHANES 2003–2004, pp. 3 – 4.

[2] Automated Blood Cell Counter: www.medscape.com

[3] Jaiwei Han, Michelinne Kamber, Data Mining : Concepts and Techniques, Morgan Kaufmann Publishers, Second Edition, 2006

[4] Margaret H.Dunham, Data Mining: Introductory and Advanced Topics, Pearson Education, 2007.

[5] Alp Aslandogan Y. and Gauri A.Mahajani, Evidence Combination in Medical Data Mining, Proceedings of the International Conference on Information Technology: Coding and Computing (ITCC’04), Volume 2, 2004, pp. 465 – 469

[6] Suguna, N. and K.G. Thanushkodi, 2011. Predicting missing attribute values using k-means clustering. Journal of Computer Science, Volume 7, issue 2, pp. 216-224.

[7] Massoud Toussi, Jean-Baptiste Lamy, Philippe Le Toumelin, and Alain Venot, Using data mining techniques to explore physicians' therapeutic decisions when clinical guidelines do not provide recommendations: methods and example for type 2 diabetes, BMC Medical Informatics and Decision Making 2009; pp. 9:28

[8] Patricia Cerrito, John C. Cerrito, Data and Text Mining the Electronic Medical Record to Improve Care and to Lower Costs, Proceedings of SUGI 31, March 26 – 29, 2006 paper 077-31, 2006

[9] Cios KJ, Moore GW, Uniqueness of Medical Data Mining, Artificial Intelligence in Medicine, 2002 Sep-Oct; 26(1-2): 2002, pp. 1- 24.

[10] Minnie D, Srinivasan S, Application of Knowledge Discovery in Database to Blood Cell Counter Data to Improve Quality Control in Clinical Pathology, Proceedings of 6th International Conference on Bio Inspired Computing – Theory and Applications 2011, September 2011, pp 338 – 342.

[11] Minnie D, Srinivasan S, Preprocessing and Genearation of Association Rules for Automated Blood Cell Counter Data in Haematology, Proceedings of International Conference on Recent Advances in Computing and Software Systems 2012, April 2012, pp 27 – 32.

[12] Minnie D, Srinivasan S, Clustering the Preprocessed Automated Blood Cell Counter Data using modified K-Means algorithms and Generation of Association Rules, International Journal of Computer Applications (IJCA), August 2012, 52(17), Foundation of Computer Science, New York, USA, pp. 38-42.

[13] Asha Gowda Karegowda, T. Vidya, Shama, M. A. Jayaram, A. S. Manjunath, Improving Performance of K-Means Clustering by Initializing Cluster Centers Using Genetic Algorithm and Entropy Based Fuzzy Clustering for Categorization of Diabetic Patients, Proceedings of International Conference on Advances in Computing, Advances in Intelligent Systems and Computing Volume 174, 2012, pp 899-904.