

PREDICTIVE ANALYSIS OF BLOOD TEST REPORT

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ABSTRACT

In modern medical applications data mining techniques are very popular and produce accurate results, diagnosing a blood test report is a complicated process that largely depends on the doctor's knowledge, experience, ability to evaluate the patient's current test results and analyze risk factors that might be causation of illness. Therefore, a need for system to assist physician in making accurate and fast decision has arisen. The main focus of the present paper is to analyze the performance of "Hierarchical clustering algorithm" for blood reports. The results are compared with the normal values given medical books and shown that the hierarchical clustering technique was sufficiently effective to diagnose medical dataset especially, blood test reports and suggested that these results may be used for developing automatic abnormality detection Expert Systems.

I. INTRODUCTION

Before modern science began to take shape in the 19th century, most doctors depended on Independent knowledge, skill and slight luck when diagnosing people. Little knowledge was Available on most common sicknesses, let alone what caused it? Doctor's knew the symptoms and possibly the name of the disease, but other than that, most physicians could do little to treat the infection, and often times, the cure appeared far more drastic than the condition itself. Not until healthcare analytics come into play did the medical field begin to comprehend what caused such problems in local citizens.

If healthcare analytics existed in the Middle Ages, avoiding the black plague may have saved millions of lives. With proper data analysis, individuals in the medical field could have pinpointed one similarity in all cases: the water. In Germany for example, many of the citizens came from different areas of the country, most of which ate different food. However, all drank the same water. Yet, those people seemingly immune to the black plague were the monks, isolated from the rest of the community in abbeys, drinking not water but beer. Modern healthcare analytics quickly would have pointed to water as the death-causing culprit, while the boiling process eliminated bacteria in the water, keeping monks healthy. Sadly, many in the medical community remain in the dark ages by not properly using healthcare analytics to determine the needs of patients and their community. This is a limitation in the current

Medical facility, resulting in poor treatment options for local patients. Data analysis obtained directly from a community is capable of identifying key needs local citizens have, what their most common ailments are, services they require and just about any other variety of information needed. It is essential for a medical provider to tailor its services towards the community and effective use of analytics turns big data into actionable information for local care providers.

Here the blood test report of the patient in structured format is given as input to the orange tool. In orange tool the blood report is analyzed and it is compared with the actual content of the blood and checked for abnormality. And then the final report is generated the report includes the detected abnormality which makes the work simple for doctor. These reports are stored in a database and it can be retrieved when needed. Updating the record can also be done here.

II. DATA ANALYTICS

Analysis of data is a process of inspecting, cleaning, transforming, and modeling data with the goal of discovering useful information, suggesting conclusions, and supporting decision-making. Especially valuable in areas rich with recorded information, analytics relies on the simultaneous application of statistics, Computer programming and operations research to quantify performance. Analytics often favors data visualization to communicate insight.

III. DATA ANALYTICS IN HEALTHCARE

Data analytics is an essential resource for any Profession. This collection of data and information is capable of forecasting the future. From understanding what services customers deem necessary to the cost effectiveness of a recently implemented technology, data analytics is a vital part of any corporation, business or organization. Analytics plays a more pivotal role for healthcare than it might in financial and business markets. Understanding data points to ever-changing trends, including new research findings, emergency situations and outbreaks of disease. Thus, effective use of analytics in the healthcare industry can improve current care but more importantly can facilitate preventive care.

IV. MODERN ANALYTICS

Before the advent of modern analytics, researchers and analysts were forced to pour over thousands of pages of data, resulting in thousands of hours of labor to make a simple conclusion based on the combined data. Often times, information was missed during this transition period, in which data was analyzed, but not to a great extent, simply because no methodology allowed large spectrums. Of data to be studied relationally. Sample groups could provide insights as to what the larger, general public might like or enjoy, but outside of these sample groups, looking over the needs for hundreds of thousands of individuals proved costly and far too time consuming. With the growth of information, big data is growing every larger, necessitating a system to create understanding from multiple data sets. A flexible platform is essential to accept multiple data sources and should have these important features:

- The ability to search information by Relationships between entities
- Index information from any source type Including social media, feeds, databases and File shares
- Ability to customize the environment based on individual needs and data sets
- Tunable search algorithms for significance, Relevance, temporal decay and geo-spatial Decay
- Simple third party integration using JSON, XML, RSS and/or KML
- Visual interface that is easy to use
- Natural language processing
- Ability to combine structured and unstructured data

V. ABOUT ORANGE

Orange is a machine learning and data mining suite for data analysis through Python scripting and visual programming. Orange library is a hierarchically-organized toolbox of data mining components. The low-level procedures at the bottom of the hierarchy, like data filtering, probability assessment and feature scoring, are assembled into higher-level algorithms, such as classification tree learning. This allows developers to easily add new functionality at any level and fuse it with the existing code. The main branches of the component hierarchy are:

Data management and preprocessing for data input and output, data filtering and sampling, imputation, feature manipulation (discretization, continuation, normalization, scaling and scoring), and feature selection, **Classification** with implementations of various supervised machine learning algorithms (trees, forests, instance-based and Bayesian approaches, rule induction), borrowing from some well-known external libraries such as LIBSVM (Chang and Lin, 2011), **Regression** including linear and lasso regression, partial least square regression, regression trees and forests, and multivariate regression splines, **Association** for association rules and frequent item sets mining, **Ensembles** implemented as wrappers for bagging, boosting, forest trees, and stacking, **Clustering**, which includes k-means and hierarchical clustering approaches, **Evaluation** with cross-validation and other sampling-based procedures, functions for scoring the quality of prediction methods, and procedures for reliability estimation, **Projections** with implementations of principal component analysis, multi-dimensional scaling and self-organizing maps.

VI. HIERARCHICAL CLUSTERING

We defined several different ways of measuring distance (ordissimilarity as the case may be) between the rows or between the columns of the datamatrix, depending on the measurement scale of the observations. As we remarked before, this process often generates tables of distances with even more numbers than the original data, but we will show now how this in fact simplifies our understanding of the data.

Distances between objects can be visualized in many simple and evocative ways. In this we shall consider a graphical representation of a matrix of distances which is perhaps the easiest to understand – a dendrogram, or tree – where the objects are joined together in a hierarchical fashion from the closest, that is most similar, to the furthest apart, that is the most different. The method of hierarchical cluster analysis is best explained by describing the algorithm, or set of instructions, which creates the dendrogram results. In this chapter we demonstrate hierarchical clustering on a small example and then list the different variants of the method that are possible.

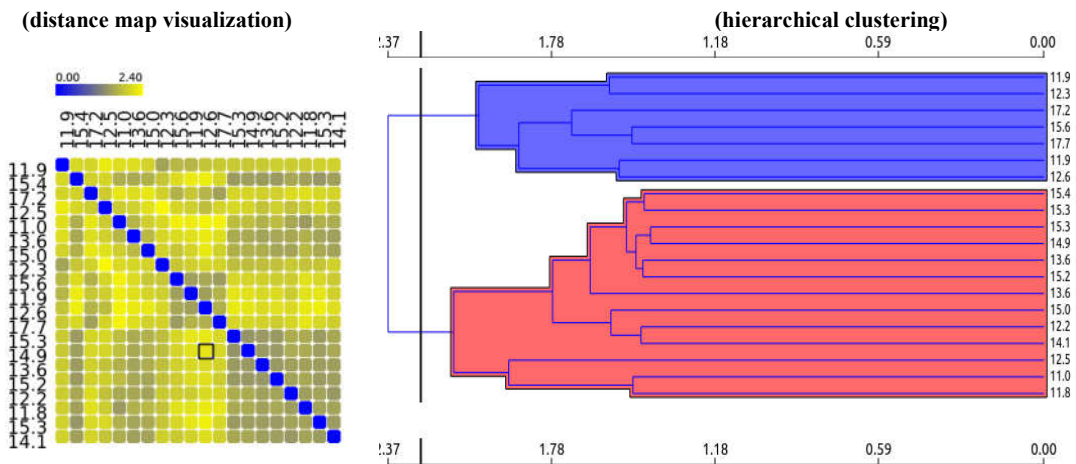
VII. METHODOLOGY

The dataset contains 20 patients' blood report with 9 attributes. Which important attributes that are used to find abnormality are hemoglobin(hg), Total cell count(tc), RedBloodCells(rbc), cholesterol(ch), and rbs.

Patient ID	Age	Gender	Height (cm)	Weight (kg)	Hemoglobin (mg/dl)	Total Cell Count (millions)	Cholesterol (mg/dl)	Red Blood Cells (millions)	RBS (mg/dl)
01	45	male	178	80	15.5	4.5	200	4.5	95
02	52	female	165	65	14.2	4.2	180	4.2	88
03	38	male	182	90	16.8	4.8	220	4.8	102
04	60	female	158	58	13.5	4.0	160	4.0	82
05	42	male	175	75	15.0	4.5	190	4.5	90
06	55	female	162	62	14.0	4.1	175	4.1	85
07	35	male	185	95	17.2	4.9	230	4.9	105
08	65	female	155	55	13.0	3.9	155	3.9	80
09	48	male	172	78	14.8	4.4	185	4.4	88
10	58	female	160	60	13.8	4.1	170	4.1	83
11	32	male	188	100	18.0	5.0	240	5.0	110
12	70	female	150	50	12.5	3.8	150	3.8	78
13	40	male	170	70	14.5	4.3	180	4.3	85
14	50	female	158	58	13.5	4.0	165	4.0	80
15	30	male	190	105	19.0	5.1	250	5.1	115
16	75	female	148	48	12.0	3.7	145	3.7	75
17	45	male	175	75	14.8	4.4	185	4.4	88
18	55	female	160	60	13.8	4.1	170	4.1	83
19	35	male	185	95	17.5	4.9	235	4.9	108
20	68	female	152	52	12.8	3.9	158	3.9	79

Fig 7.1 Input for the process

The given data set is converted into table structure and the map distance is founded for that data's by comparing each data for the single attribute. If the map distance was found then the data will be visualized and the distance matrix for the particular attribute data will be obtained. The data's will be clustered in the form of hierarchical. The similar set of data will be combined together and the dissimilar set of data will be combined together. Then again the clustered data will be converted in the form of table. In that it separate the abnormality with normality values.



VIII. RESULT

	AGE	GENDER	hb(in gms)	tc(in lakhs)	tbc(in millions)	iolestral(mg/c)	urea(mg/dl)	HC_class
1	28	male	11.9	5567	4.6	130	10	Cluster 0
2	15	male	12.3	4321	3.7	158	13	Cluster 0
3	45	male	17.2	6023	4.2	259	35	Cluster 0
4	37	male	15.6	9635	4.6	196	17	Cluster 0
5	42	male	17.7	8695	4.4	223	23	Cluster 0
6	39	male	11.9	10325	4.8	201	20	Cluster 0
7	44	male	12.6	8546	5.0	265	22	Cluster 0
8	29	female	15.4	4996	3.3	169	30	Cluster 1
9	29	female	15.3	5698	3.5	138	30	Cluster 1
10	18	female	15.3	4586	3.9	161	25	Cluster 1
11	16	female	14.9	4965	4.0	165	26	Cluster 1
12	23	female	13.6	5698	3.8	189	29	Cluster 1
13	21	female	15.2	6324	3.7	179	24	Cluster 1
14	21	female	13.6	7236	3.8	158	52	Cluster 1
15	26	female	15.0	9546	3.6	139	12	Cluster 1
16	36	female	12.2	7965	3.6	165	26	Cluster 1
17	36	female	14.1	7896	3.6	156	33	Cluster 1
18	60	female	12.5	7362	4.8	266	36	Cluster 1
19	54	female	11.0	4886	3.3	152	40	Cluster 1
20	41	female	11.8	4932	3.4	156	27	Cluster 1

The blood report will be analyzed and using hierarchical clustering algorithm the data will be clustered and it define a similar and dissimilar value separated and the resulting table had same value. There is an additional information called cluster. If the row had a cluster 0 value there is an abnormality in the blood. If the row had cluster 1 value there is no abnormality in the particular person's blood.

XI. BENEFITS

1. Finding the abnormality of patients from many test records will be easy.
2. There is no need of doctor's knowledge to understand the report.
3. Work load for doctor's must be reduced instead of analyzing the report.
4. Reports of patient will be maintained and updated for various testing purposes.

X. CONCLUSION

The performance evaluation is conducted with respect to the performance parameter: Accuracy and found that the Proposed Hierarchical Clustering Algorithm applied on Data set exhibits more accurate using classification. These results are used in developing the blood report automation Expert system for decision making in diagnosing the by both patients and doctors. The details of the proposed expert system are included in this paper.

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