

A Comprehensive and Experimental Survey on Medical Data Classification and Pattern Recognition

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ABSTRACT

This paper is proposed to compare and analyze various type of medical data classification and pattern recognition methods. Medical data classification methods majorly divided into three categories such as supervised, classification and also semi-supervised classification. Pattern recognition and data classifications are both overlapped domain for useful knowledge generation and prediction from training data. The field of medical diagnosis (or) clinical support system needs in intelligent data classification and pattern recognition algorithms for more accuracy in clinical decision making. Supervised classification, KNN probabilistic neural network, SVM and more, combination of supervised classification called as ensemble algorithm. These types of mixed algorithm provide more accuracy. Unsupervised classification also contains some types such as K-means, deep learning methods, hierarchical clustering and more. In this paper we have to analyze various types of classification algorithms using sample medical record of upper abdomen diseases database. In this paper we have to analyze maximum of algorithms in experimental using same training data, this will used for various performance and accuracy analysis.

Keywords : Medical support system, clinical support system, medical data classification, supervised classification, un-supervised classification, rule-based classification, DCT ,Bayesian classification, PNN artificial neural network adaptive classifier, K-NN, K-means, machine learning, svm, abdominal diseases.

I. INTRODUCTION

Medical data contains large volume of information in an unstructured format, data mining discovers insightful, important and good patterns which are descriptive, understandable and predictive from large amount of data[1].

Data mining includes important techniques such as association, clustering, classification and prediction[6][7].

Classification is also one of the most important techniques in mining process[10][11]. The challenge

in knowledge discovery is constructing fast and accurate classifier for large data set [2].Medical data mining is an trending technology in medical field that solves the most traditional problems, such as congestion long wait time and delayed patient use. Clinical support systems help doctors to make accurate diagnosis of most diseases. Most medical data sets are widely distributed and unclassified medical data also look like heterogeneous and huge size/volume[8][9].

These data need to be organized in a form which is classified and understandable. Advantages of using data mining techniques in medical domain is to improve the accuracy of the output with large amount of data. Medical data mining has great potential for exploring useful patterns among medical data set. Knowledge generation and retrieval are performed using classification algorithms, data mining and artificial neural networks. In this paper we have to analyze various types of data classification algorithm in chapter 5, Introduction to pattern recognition in chapter 2, and comparison and analysis on chapter 7 and 8.

II. PATTERN RECOGNITION

Recognizing different types of objects in real world environment is a complex task for humans. To overcome this problem we have to implement artificial (or) computerizing methods[15]. Because in computers pattern recognition and machine learning not developed well. Pattern recognition methods provide solution for various problems such as bioinformatics. document analysis, industrial automation, image analysis, remote sensing, handwritten text analysis, medical diagnosis, speech recognition, IS and many more. Pattern recognition mostly involved in three steps one is extracting features from given information and second one is classifying extracted patterns using specific methods[17][18].

Third one is data acquisition. Data acquisition is the process of converting information from one form to system readable-digital form, for example computer systems can handle different types of data such as audio-speech, text-character, picture- image. Data acquisition is performed by different types of sensors, such as mic-audio (or)speech, cosensor, LDR-light sensor, scanner-image and more pattern recognition training performed by train data and system performance tested by test data.

III. CLASSIFICATION

It's a process for updating (or) adding unlabeled data point to labeled classified data group. Unlabeled data recognized and organized to labeled classified data using various classification methods(9). Devising a procedure for classification in which exact classes are known in advanced termed as pattern recognition(or) supervised learning[23][25].

In un-supervised learning classification classes not known in advance. There are three standard classification techniques available, such as machine learning based classification, statistical based classification and neural network based classification. These types of classification algorithms further subdivided (or) contains both supervised and unsupervised methods[32][29].

IV. SAMPLE DATA

In this paper we have used upper abdomen diseases data set, this training and testing data set contains sample of 10 disease for training and 10 disease for testing (noisy (or) un classified data).

T-L1- 1

| | Table 1 | | | | | | | |
|-------|----------------------------------|----------------------------------|-------|--|--|--|--|--|
| DISEA | DISEASENA | ADDDESCRI | DISEA | SYMPTO | | | | |
| SEID | ME | PTION | SEID1 | MNAME | | | | |
| 1001 | ESTINAL | GUSTROINT ESTINAL BLEEDING | 1001 | BLEEDIN G | | | | |
| 1001 | GUSTROINT ESTINAL BLEEDING | GUSTROINT ESTINAL BLEEDING | 1001 | RED COLORE D VOMIT | | | | |
| 1001 | GUSTROINT ESTINAL BLEEDING | GUSTROINT ESTINAL BLEEDING | 1001 | COFFEE GROUND S COLORE D VOMIT | | | | |
| 1002 | FOOD | FOOD | 1002 | VOMITIN | | | | |

4.1 SAMPLE DATA- TRAINING SET

| | POISONING | POISONING | | G | | ANXIETY | ANXIETY | | |
|------|--|--|--------|---------------------------|------|----------------------|--|------|---------------------------------------|
| 1000 | FOOD | FOOD | 1.0.00 | DIARRHE | | DISORDER | DISORDER | | |
| 1002 | | POISONING | 1002 | A | 1005 | INTESTINA L LIEUS | INTESTINA L LIEUS | 1005 | PAIN |
| 1002 | FOOD POISONING | FOOD POISONING | 1002 | PAIN | | | INTESTINA | | DECREAS |
| 1003 | GASTROEN TERITIS | STOMACH FLUE | 1003 | VOMITIN G | 1005 | L LIEUS | L LIEUS | 1005 | ED APPETITE |
| 1003 | GASTROEN TERITIS | STOMACH FLUE | 1003 | PAIN | 1005 | INTESTINA L LIEUS | INTESTINA L LIEUS | 1005 | CONSTIP ATION |
| 1003 | GASTROEN TERITIS | STOMACH Flue | 1003 | BLOATIN G | 1005 | INTESTINA L LIEUS | INTESTINA L LIEUS | 1005 | VOMITIN G |
| 1003 | GASTROEN TERITIS | STOMACH FLUE | 1003 | DECREAS ED APPETITE | 1005 | INTESTINA L LIEUS | INTESTINA L LIEUS | 1005 | STOMAC H CRAMPS |
| 1003 | GASTROEN TERITIS | STOMACH FLUE | 1003 | DIARRHE A | 1006 | BOWEL | IRRITABLE BOWEL SYNDROME | 1006 | BLOATIN G |
| 1003 | GASTROEN TERITIS | STOMACH Flue | 1003 | RED COLORE D VOMIT | 1006 | IRRITABLE BOWEL | IRRITABLE | 1006 | DIARRHE A |
| 1004 | ED ANXIETY DISORDER | GENERALIZ ED ANXIETY DISORDER | 1004 | CHILLS | 1006 | | IRRITABLE | 1006 | FREQUEN T URGE TO HAVE BOWEL |
| 1004 | ED ANXIETY | ANXIETY | 1004 | PAIN | | SYNDROME | SYNDROME | | MOVEME NT |
| 1004 | DISORDER GENERALIZ ED ANXIETY | DISORDER GENERALIZ ED ANXIETY | 1004 | ANXIETY | 1006 | BOWEL | IRRITABLE BOWEL SYNDROME | 1006 | INCREAS ED PASSING GAS |
| | GENERALIZ | DISORDER GENERALIZ ED | | DIZZINES | 1006 | BOWEL | IRRITABLE BOWEL SYNDROME | 1006 | PAIN |
| 1004 | ED ANXIETY DISORDER | ANXIETY DISORDER | 1004 | S | 1006 | IRRITABLE BOWEL | IRRITABLE BOWEL | 1006 | CONSTIP ATION |
| 1004 | ED ANXIETY DISORDER | GENERALIZ ED ANXIETY DISORDER | 1004 | VOMITIN G | 1006 | IRRITABLE BOWEL | SYNDROME IRRITABLE BOWEL SYNDROME | 1006 | FREQUEN T BOWEL MOVEME |
| 1004 | GENERALIZ ED | GENERALIZ ED | 1004 | AGITATI ON | 1007 | NARCOTIC | OPIATE | 1007 | NT PAIN |

| | ABUSE | ADDICTION | | |
|------|----------|-----------|------|----------|
| | NARCOTIC | OPIATE | | CONFUSI |
| 1007 | ABUSE | ADDICTION | 1007 | ON |
| | NARCOTIC | OPIATE | | CONSTIP |
| 1007 | ABUSE | ADDICTION | 1007 | ATION |
| | NARCOTIC | OPIATE | | VOMITIN |
| 1007 | ABUSE | ADDICTION | 1007 | G |
| | NARCOTIC | OPIATE | | GIDDINE |
| 1007 | ABUSE | ADDICTION | 1007 | SS |
| | | | | ITCHING |
| 1007 | NARCOTIC | OPIATE | 1007 | AND |
| | ABUSE | ADDICTION | | BURNING |
| 1000 | PANIC | PANIC | 1000 | |
| 1008 | ATTACKS | DISORDER | 1008 | ANXIETY |
| 1000 | PANIC | PANIC | 1000 | DIZZINES |
| 1008 | ATTACKS | DISORDER | 1008 | S |
| 1000 | PANIC | PANIC | 1000 | VOMITIN |
| 1008 | ATTACKS | DISORDER | 1008 | G |
| 1008 | PANIC | PANIC | 1000 | GIDDINE |
| | ATTACKS | DISORDER | 1008 | SS |
| | | | 1008 | IRREGUL |
| 1008 | PANIC | PANIC | | AR |
| 1008 | ATTACKS | DISORDER | | HEART |
| | | | | BEAT |
| 1008 | PANIC | PANIC | 1008 | PAIN |
| 1000 | ATTACKS | DISORDER | 1000 | |
| | PEPTIC | PEPTIC | | RED |
| 1009 | ULCER | ULCER | 1009 | COLORE |
| | OLGER | | | D VOMIT |
| | PEPTIC | PEPTIC | | BLACK |
| 1009 | ULCER | ULCER | 1009 | COLORE |
| | | | | D STOOLS |
| 1009 | PEPTIC | PEPTIC | 1009 | WEIGHT |
| | ULCER | ULCER | | LOSS |
| 1009 | PEPTIC | PEPTIC | 1009 | VOMITIN |
| | ULCER | ULCER | | G |
| | PEPTIC | PEPTIC | | RED |
| 1009 | ULCER | ULCER | 1009 | COLORE |
| | | | | D STOOLS |
| 1009 | PEPTIC | PEPTIC | 1009 | PAIN |

| | ULCER | ULCER | | |
|------|-------------------|-------------------|------|-----------------------------|
| 1010 | IRON POISONING | IRON POISONING | 1010 | RED COLORE D VOMIT |
| 1010 | IRON POISONING | IRON POISONING | 1010 | PAIN |
| 1010 | IRON POISONING | IRON POISONING | 1010 | DIARRHE A |
| 1010 | IRON POISONING | IRON POISONING | 1010 | BLACK COLORE D STOOLS |
| 1010 | IRON POISONING | IRON POISONING | 1010 | RED COLORE D STOOLS |

V. TYPES OF DATA CLASSIFICATION ALGORITHM

The data classification algorithms are broadly classified into two categories:

1) Supervised Classification

Supervised learning of data classification method works based on pre-defined static rules and validated using test data. Supervised classification is most suitable for simple problems[41].Supervised classification algorithm is further sub divided into semi-supervised. This type of classification algorithm is most suitable for simple and moderate problem[36][35].

List of Supervised and Semi-supervised Classification Algorithm

- 1. Rule Based Classification
- 2. Decision Tree Classification
- 3. Bayesian Classification
- 4. Adaptive Classifier
- 5. Neural Network
- 6. .K-NN
- 7. SVM

2) Un-Supervised(or) Automatic Classification

Un-supervised classification is performed without the interaction or control of user. Un-supervised classification is widely used for most complex data analysis. This types of classification is performed in dynamic manner and creates feature extractions and patters automatically [2][38][39].

List of Un-Supervised Algorithm

1.Partioned Clustering

2. Hierarical Clustering.

3. Density Based Clustering.

VI. EXISTING METHODS

6.1 RULE BASED CLASSIFICATION

Rule Based Classification performs based on simple ifelse-end conditional model. Every traditional programming language provide conditional statement such as if—else. Syntax for rule based classification model is follows.[1]

If (Condition) Then Statement 1 to n END

This method is used to perform simple problems, easy to program, easy to understand by others and also it renders decent performance [15][1][14].

Classification Example

IF symptom0=BLEEDING Then weight=weight+1 End If symptom1=COFFEE COLORED IF GROUNDS VOMIT Then weight=weight+1 End If IF symptom2=RED COLORED VOMIT Then weight=weight+1 End If If weight=countofsysmptoms Then DiseaseName=GUSTROINTESTINAL BLEEDING End If ******************END OF RULE***********************

IF symptom0=DIARRHEA Then weight=weight+1 End If IF symptom1=PAIN Then weight=weight+1 End If IF symptom2=VOMITING Then weight=weight+1 End If If weight=countofsysmptoms Then DiseaseName=FOOD POISONING End If ****************************

TEST DATA OUTPUT

Disease Identified **GUSTROINTESTINAL** : BLEEDING Disease Identified : FOOD POISONING Disease Identified : GENERALIZED ANXIETY DISORDER Disease Identified : INTESTINAL LIEUS Identified Disease **IRRITABLE** BOWEL : **SYNDROME** Disease Identified : PEPTIC ULCER Disease Identified : IRON POISONING **Total Input Records :10** Total Success Count :7 Success Percentage :70 %

6.2 DECISION-TREE CLASSIFICATION

Decision Tree Classification works based on decision tree induction. It may similar to rule based classification, combined with tree, but have many advantages then rule based classification. Decision tree represented in graph structure and contains secondary leafs and nodes, the top most node is called root node.[1][14][47][46][44]

Information Gain for Class D

$$Info(D) = -\sum_{i=1}^{m} p_i \log_2(p_i)$$

Information Gain for Attribute A

$$Info_{A}(D) = \sum_{j=1}^{v} \frac{|D_{j}|}{|D|} \times Info(D_{j})$$

Information Gain

$$Gain(A) = Info(D) - Info_A(D)$$

Classification Example :

| DiseaseID | DiseaseName | Symptom 1 | Symptom 2 | Symptom 3 | Symptom 4 | Symptom 5 | Symptom 6 | Symptom 7 | Symptom 8 | Condition |
|-----------|---------------------------------|--------------|---------------------------------------|-------------------------|-------------------------------|-------------------------|-----------------------------|--------------|--------------|-----------|
| 1001 | GUSTROINTESTINAL BLEEDING | BLEEDING | COFFEE GROUNDS COLORED VOMIT | RED COLORED VOMIT | NIL | NIL | NIL | NIL | NIL | YES |
| 1002 | FOOD POISONING | DIARRHEA | PAIN | VOMITING | NIL | NIL | NIL | NIL | NIL | YES |
| 1003 | GASTROENTERITIS | BLOATING | DECREASED APPETITE | DIARRHEA | PAIN | RED COLORED VOMIT | VOMITING | NIL | NIL | YES |
| 1004 | GENERALIZED ANXIETY DISORDER | AGITATION | ANXIETY | CHILLS | DIZZINESS | PAIN | VOMITING | NIL | NIL | YES |
| 1005 | INTESTINAL LIEUS | CONSTIPATION | DECREASED APPETITE | PAIN | STOMACH CRAMPS | VOMITING | NIL | NIL | NIL | YES |
| 1007 | NARCOTIC ABUSE | CONFUSION | CONSTIPATION | | ITCHING AND BURNING | PAIN | VOMITING | NIL | NIL | YES |
| 1006 | IRRITABLE BOWEL SYNDROME | BLOATING | CONSTIPATION | | FREQUENT BOWEL MOVEMENT | HAVE | INCREASED PASSING GAS | PAIN | NIL | YES |
| 1008 | PANIC ATTACKS | ANXIETY | DIZZINESS | GIDDINESS | IRREGULAR HEART BEAT | PAIN | VOMITING | NIL | NIL | YES |

Figure 1. Decision Tree

TEST DATA OUTPUT

| Disease | Identified | : | GUSTROIN | TESTINAL | | | |
|-------------------------------------|-----------------------------|------|-----------|----------|--|--|--|
| BLEEDING | | | | | | | |
| Disease Identified : FOOD POISONING | | | | | | | |
| Disease | Identified : | GE | NERALIZED | ANXIETY | | | |
| DISORD | ER | | | | | | |
| Disease I | dentified : INT | ESTI | NAL LIEUS | | | | |
| Disease | Identified | : | IRRITABLE | BOWEL | | | |
| SYNDRC | OME | | | | | | |
| Disease I | dentified : PEP | TIC | ULCER | | | | |
| Disease I | dentified : IRO | N PC | DISONING | | | | |
| Total Inp | out Records :10 | | | | | | |
| Total Suc | Total Success Count :7 | | | | | | |
| Success F | Percentage :70 ^o | % | | | | | |
| | | | | | | | |
| | | | | | | | |

6.3 BAYESIAN CLASSIFICATION

Bayesian classification works based on bayes theorem, probability and class frequency. It is better than DT Classification and Rule based classification.[1][2][63][86][87]

Bays theorem as follows

$$P(H/\mathbf{X}) = \frac{P(\mathbf{X}/H) P(H)}{P(\mathbf{X})}$$

Disease Name : GUSTROINTESTINAL BLEEDING

| Attribute Name | Attribute Value | postivefreq | negativefreq |
|----------------|------------------------------|-------------|--------------|
| Symptom1 | BLEEDING | 2 | 0 |
| Symptom1 | BLACK COLORED STOOLS | 0 | 1 |
| Symptom1 | DIARRHEA | 0 | 1 |
| Attribute Name | Attribute Value | postivefreq | negativefreq |
| Symptom2 | PAIN | 0 | 1 |
| Symptom2 | RED COLORED VOMIT | 1 | 0 |
| Symptom2 | DIARRHEA | 0 | 1 |
| Symptom2 | COFFEE GROUNDS COLORED VOMIT | 1 | 0 |
| Attribute Name | Attribute Value | postivefreq | negativefreq |
| Symptom3 | RED COLORED VOMIT | 1 | 0 |
| Symptom3 | PAIN | 0 | 1 |
| Symptom3 | VOMITING | 0 | 1 |
| Symptom3 | COFFEE GROUNDS COLORED VOMIT | 1 | 0 |
| Attribute Name | Attribute Value | postivefreq | negativefreq |
| Symptom4 | RED COLORED STOOLS | 0 | 1 |
| Attribute Name | Attribute Value | postivefreq | negativefreq |
| Symptom5 | RED COLORED VOMIT | 0 | 1 |

Table 2. Bayesian Classification Example

TEST DATA OUTPUT

| Disease | Identified | : | GUSTROIN | TESTINAL | | | | |
|--|--|-------|----------------|----------|--|--|--|--|
| BLEEDING | | | | | | | | |
| Positive 1 | Positive Probability:104 Negative Probability:39 | | | | | | | |
| Disease I | dentified : FOO | D PC | DISONING | | | | | |
| Positive 1 | Probability:40 N | Vegat | ive Probabilit | y:0 | | | | |
| Disease I | dentified : GAS | TRO | ENTERITIS | | | | | |
| Positive 1 | Probability:48 N | Vegat | ive Probabilit | y:0 | | | | |
| Disease | Identified : | GEN | NERALIZED | ANXIETY | | | | |
| DISORD | ER | | | | | | | |
| Positive Probability:48 Negative Probability:0 | | | | | | | | |
| Disease Identified : INTESTINAL LIEUS | | | | | | | | |
| Positive Probability:40 Negative Probability:0 | | | | | | | | |

Identified BOWEL Disease IRRITABLE ٠ **SYNDROME** Positive Probability:56 Negative Probability:0 **Disease Identified : PANIC ATTACKS** Positive Probability:15 Negative Probability:0 Disease Identified : PEPTIC ULCER Positive Probability:12 Negative Probability:0 Disease Identified : NARCOTIC ABUSE Positive Probability:12 Negative Probability:0 Disease Identified : IRON POISONING Positive Probability:20 Negative Probability:0 Total Input Records :10 Total Success Count :10 Success Percentage :100 %

Get Training Data Get Training Data Naiv Bays Calculate Probebility of each attribute Calculate Probebility of each attribute Calculate Probebility table Store output data to data store Store

ALGORITHM FOR NAVI BAYES CLASSIFICATION Step 1: START

Step 2: Get disease (or)patient record as table->ITB

Step 3: Calculate probability table for (ITB)->Attribute table(Frequency table)

Step 4:Calculate negative and positive probability table->FPT

Step 5: Test with test data(FPT,Test Data)->Output

Step 6: Check for positive and negative probabilityvaluewhich is higher

Step 7: If (Positive> Negative) then

Show output class as positive else

Show output Class as negative

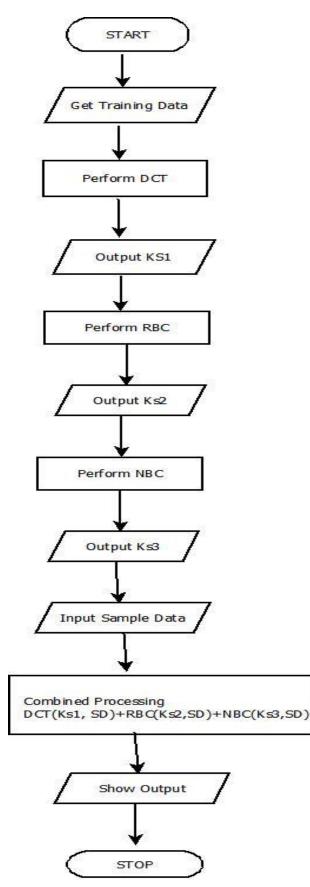
Step 8: END

6.4 ADAPTIVE CLASSIFIER

Adaptive classifier contains combined future of rulebased classification, decision tree classification and Bayesian classification. This algorithm is derived by combining the above three algorithms. Adaptive classifier perform well in medical data classification.[1][86][63].

Algorithm for Adaptive Classifier

Step 1:Start Step 2:Get Training data->TD Step 3:Perform DCT(TD)->KS1 Step 4:Perform RBC(TD)-KS2 Step 5:Perform NB(TD)-KS3 Step 6:Get Sample Test Data->STD Step 7:Perform DCT(STD,TD)->OT1 Step 8:Perform RBC(STD,TD)->OT2 Step 9:Perform NB(STD,TD)->OT3 Step 10:Combine(OT1,OT2,OT3)->FT Step 12: END



TEST DATA OUTPUT Based :GUSTROINTESTINAL BLEEDING Rule Identified DTC Based :GUSTROINTESTINAL BLEEDING Identified NBC Based :GUSTROINTESTINAL BLEEDING Identified Rule Based : FOOD POISONING Identified DTC Based :FOOD POISONING Identified NBC Based :FOOD POISONING Identified NBC Based :GASTROENTERITIS Identified Rule Based :GENERALIZED ANXIETY DISORDER Identified DTC Based :GENERALIZED ANXIETY DISORDER Identified NBC Based :GENERALIZED ANXIETY DISORDER Identified Rule Based :INTESTINAL LIEUS Identified DTC Based :INTESTINAL LIEUS Identified NBC Based :INTESTINAL LIEUS Identified Rule Based : IRRITABLE BOWEL SYNDROME Identified DTC Based :IRRITABLE BOWEL SYNDROME Identified NBC Based :IRRITABLE BOWEL SYNDROME Identified NBC Based : PANIC ATTACKS Identified Rule Based : PEPTIC ULCER Identified DTC Based : PEPTIC ULCER Identified NBC Based : PEPTIC ULCER Identified NBC Based :NARCOTIC ABUSE Identified Rule Based : IRON POISONING Identified DTC Based :IRON POISONING Identified NBC Based :IRON POISONING Identified Total Input Records :10 Total Success Count :7 Success Percentage :70 % Total Positive Count :24 **Total Negative Count :6** Total True Positive Count :7 Total True Negative Count :3

6.5 NEURAL NETWORK

Artificial Neural Network works based on biological nervous system. Artificial neural network classification algorithm uses gradient decent method, Neural network contains multiple neurons for combined processing, neural network has two phases training and testing, formerly neural networks used for classification and pattern recognition.[5][24][29]

Neural network natively dynamic because its dynamically changes its structure and weights between neurons. Weight adjustment is performed for minimizing errors. Weight adjustment performed based on input and output of current training phase. In ANN multiclass problems are solved by multilayer feed forward network, to identify chest disease by implementing probabilistic neural networks[59]and show diagnostic of various multi layer neural network[59][48][61].

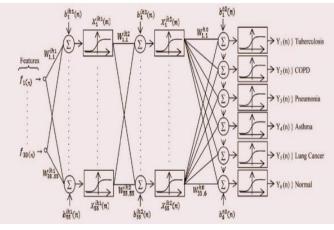


Figure 3. Classification of Chest Diseases using Multilayer Neural Network

4.6 K-NN

This method is mostly used in pattern recognition. K –nearest neighborhood method is used for both classification and regression analysis [4][40][41][42].

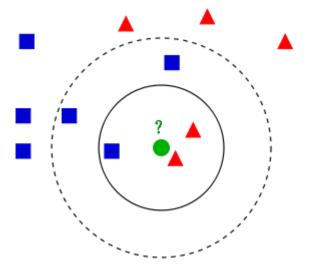


Figure 4. Example of k-NN classification

The test sample (green circle) should be classified either to the first class of blue squares or to the second class of red triangles. If k = 3 (solid line circle) it is assigned to the second class because there are 2 triangles and only 1 square inside the inner circle. If k = 5 (dashed line circle) it is assigned to the first class (3 squares vs. 2 triangles inside the outer circle).

TEST DATA OUTPUT

Expected Name:GUSTROINTESTINAL Disease BLEEDING :BLEEDING,COFFEE GROUNDS Symptoms COLORED VOMIT, RED COLORED VOMIT,,,,, Distance with :GUSTROINTESTINAL BLEEDING : 0 Distance with :INTESTINAL LIEUS : 11344.1157874909 Distance with : PEPTIC ULCER : 13893.9396500777 Distance with :GASTROENTERITIS • 13891.0517240416 Distance :NARCOTIC with ABUSE ٠ 13889.3179458172 Distance with :FOOD POISONING • 14.0356688476182 Distance with :GENERALIZED ANXIETY DISORDER: 13885.8628828028 Distance with :IRRITABLE BOWEL SYNDROME : 16029.0039303757 POISONING Distance with :IRON : 11341.2866113153

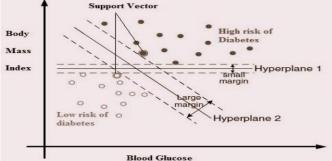
Distance with :PANIC ATTACKS : 13888.741087658 Min Distance Obtained:GUSTROINTESTINAL **BLEEDING** Expected Disease Name: FOOD POISONING Symptoms : DIARRHEA, PAIN, VOMITING,,,,, Distance with :GUSTROINTESTINAL BLEEDING : 14.0356688476182 Distance with :INTESTINAL LIEUS • 11344.1185642605 Distance with :PEPTIC ULCER : 13893.9370230327 :GASTROENTERITIS Distance with : 13891.0571591942 :NARCOTIC ABUSE Distance with 13889.3221576865 Distance with :FOOD POISONING : 0 Distance with :GENERALIZED ANXIETY DISORDER: 13885.8779700817 Distance with :IRRITABLE BOWEL SYNDROME : 16029.0093892293 Distance :IRON POISONING with 11341.2920339792 Distance with :PANIC ATTACKS : 13888.7457317067

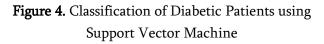
Min Distance Obtained: FOOD POISONING

2222226.7 SVM

SVM is invented by vapnik etal based on statistical learning. SVM method initially support binary classification, further it could be extended for multi class problems. SVM creates hyper plane for single dimension problem and multiple hyper plan for multiple problems. These make SVM most familiar, and produces hyper plane from given input space and separate data points as different classes. Data separation done via original finite dimensional space into new higher dimension space[50][51][52].

Kernel function are used for non-linear mapping of training sample to high dimensional space. Different types of kernel functions available such as Gaussian, polynomial, sigmoid, etc.. In short SVM separate input data points into hyper plane, hyper plane constructed with the help of support vectors. SVM support both linear and non-linear data separation[55][56][67].





Introduction to Clustering

Clustering comes under the category of unsupervised learning method, clustering different from classification because classification most relevant to supervised and clusters based on data point similarity between given data points. There are many clustering algorithms available for various problems. For example gene expression data clustering using hieratical and genetic algorithm approach[68][72].

6.8 PARTIONED CLUSTERING

In this clustering unknown or unlabeled data set, n data points portioned into K Clusters each clusters must contains one data points and each data point must hooked to one cluster. In this method we need to define k-number of cluster in initial stage partition of clustering, further divided into two major methods such as k-means and k-mediods[71][74] . k-means method is an widely adopted and enhanced periodically. in k-means n data points into k-cluster using Euclidian distance between data points and cluster. Distance of data point and different clusters may vary short distance with cluster center taken as friend for categorization[5][68].

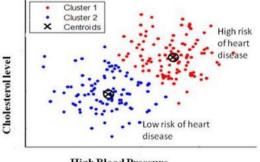
Pseudo code for K-means algorithm:

- Step 1: Start
- Step 2: Get number of clusters-> NC
- Step 3: Get number iterations->NI
- Step 4: Calculate initial centroids(NC,NI)->IC
- Step 5: Calculate Euclidian distance(data items IC)
- Step 6: Cluster data items(IC,Data items)

Step 7: Check for centroid relocation(IC,Data items)->RC

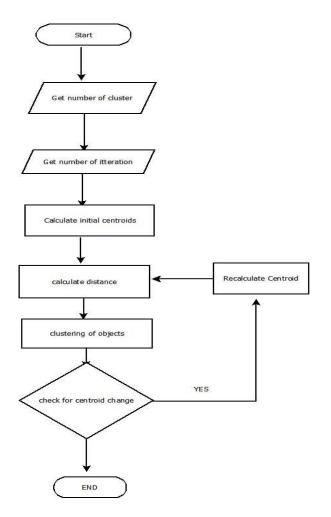
Step 8: End

For Example discovered the causes of risk related with fluoride content in drinking water using k-means algorithm[73].figure k means shows high blood pressure and cholesterol using k-means clustering.



High Blood Pressure

Figure 5. Example for K-Means Algorithm for Indentifying High Blood Pressure and cholesterol .



6.9 HIERARCHICAL CLUSTERING.

In Hierarchical clustering we don't need to input nnumber of clusters in advance. Hierarchical clustering portioning done via Hierarchical way[75]. There is two way available one is top-up approach and another one is bottom up approach. Hierarchal clustering further sub-divided into two categories agglomerative and another one is divisive method. Agglomerative check the input data point to any relevant subcategory or cluster and hook to that cluster. Agglomerative frequently check if the data point only attached to one subcategory and need termination condition for each data point[5]. Divisive method opposite to agglomerative, in divisive all data points initially subdivided into two large sub categories, then further sub divided into two recursively, to hierarchal complete divisive clustering need termination condition[76][77].

Mixed clustering methods provide more performance, for example combine k-means and hierarchical approach to cluster micro – array data gives better performance than expected.[76] Another example in fig two cluster of 192-gene expression data[78] to identify disease.

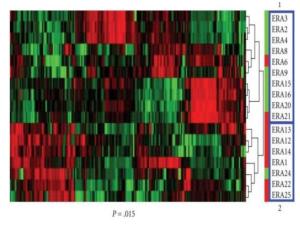


Figure 6. Hierarchical Clustering for Grouping the Patients into Two Cluster using 192-gene Expression Profile [78]

6.10.DENSITY BASED CLUSTERING

Density based clustering contains many advantages than hierarcial and portioned based clustering hierarchal clustering only handle spherical type data problems. But not to handle outlier and arbitra shaped data. Density based clustering handle be arbitrary and outlier problems. There is an two m familiar methods available one is DBSCAN a another one is OPTICS to density cluster data.[79][' DENCLUE is an another method for density bas data clustering[5].Figure [79] Provide un healthy si clustering of wounded skin using DBSCAN Algorith

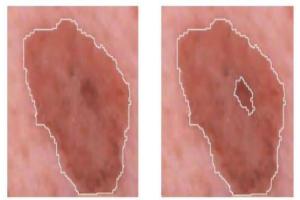


Figure 7. Clustering of Skin Wound Image using DBSCAN

VII. COMPARATIVE TABLE (SUPERVISED)

| | | | | | 3. As compare |
|---------------|------------------|---------------------|--------|-----------|---------------|
| Methods | Advantage | Disadvantage | | | other meth |
| K-NN | 1. It is easy to | 1. It requires | | | training pro |
| | implement. | large storage | | | take m |
| | 2. Training is | • • | | | time. |
| | done in faster | 2. Sensitive to | | | 4. SVM |
| | manner. | noise. | | | designed |
| | | 3. Testing is | | | solve |
| | | slow. | | | the problem |
| Decision Tree | 1. There are no | 1. It is restricted | | | binary class. |
| | requirements of | | | | solves |
| | domain | attribute. | | | problem |
| | knowledge in | 2. It generates | | | multi |
| | the | categorical | | | class |
| | construction of | output. | | | breaking it i |
| | decision tree. | 3. It is an | | | pair |
| | 2. It minimizes | unstable | | | of two clas |
| | the ambiguity | classifier i.e. | | | such |
| | of | performance of | | | oneagainst-or |
| | complicated | classifier is | | | and o |
| | decisions and | depend upon | | | againstall. |
| | assigns | the type of | Neural | 1. Easily | 1. Local mini |

| rary | | exact values to | dataset. |
|------|---------|-------------------|-------------------|
| oth | | outcomes of | 4. If the type of |
| 10st | | various actions. | dataset is |
| and | | 3. It can easily | numeric than it |
| | | process the data | generates a |
| [72] | | with | complex |
| ised | | high dimension. | decision tree |
| skin | | 4. It is easy to | |
| .hm. | | interpret. | |
| | | 5. Decision tree | |
| | | also handles | |
| | | both | |
| | | numerical and | |
| | | categorical data. | |
| | Support | 1. Better | 1. |
| | Vector | Accuracy as | Computationally |
| | Machine | compare to | expensive. |
| | | other classifier. | 2. The main |
| | | 2. Easily handle | problem is the |
| | | complex | selection of |
| 5 | | nonlinear | right kernel |
| | | data points. | function. For |
| | | 3. Over fitting | • |
| | | problem is not | different kernel |
| | | as much | function |
| | | as other | shows different |
| | | methods. | results. |
| | | | 3. As compare to |
| | | | other methods |
| ires | | | training process |
| age | | | take more |
| | | | time. |
| to | | | 4. SVM was |
| | | | designed to |
| is | | | solve |
| | | | the problem of |
| cted | | | binary class. It |
| put | | | solves the |
| | | | problem of |
| ates | | | multi |
| | | | class by |
| | | | breaking it into |
| an | | | pair |
| | | | of two classes |
| i.e. | | | such as |
| of | | | oneagainst-one |
| is | | | and one- |
| pon | | | againstall. |
| of | Neural | 1. Easily | 1. Local minima. |
| | | | |

R. Subathra Devi et al. Int J S Res Sci. Engg. Tech. 2018 Mar-Apr;4(4): 1520-1537

| Network | identify | 2. Over-fitting. | | the | selection of |
|-------------------------|--------------------|-------------------|------------|------------------|------------------|
| TICLWUIK | , | 0 | | | |
| | complex | 3. The | | number of | merge or split |
| | relationships | processing of | | clusters in | point. Once a |
| | between | ANN | | advance. | decision is made |
| | dependent | network is | | | it cannot be |
| | and | difficult to | | | undone. |
| | independent | interpret | | | 3. Not work |
| | variables. | and require high | | | well in the |
| | 2. Able to | processing | | | presence of |
| | handle noisy | time if there are | | | noise and |
| | data. | large neural | | | outlier. |
| | | networks. | | | 4. Not scalable. |
| Bayesian | 1. It makes | 1. It does not | Density | 1. No need to | 1. Not handle |
| Belief | computations | give accurate | Based | specify number | the data points |
| Network | process | results in some | Clustering | of | with |
| | easier. | cases where | | cluster in | varying |
| | 2. Have better | there exists | | advance. | densities. |
| | speed and | dependency | | 2. Easily handle | 2. Results |
| | accuracy for | among variables. | | cluster with | depend on the |
| | huge datasets. | | | arbitrary shape. | distance |
| | | | | 3. Worked well | measure. |
| V | III. COMPARATIVE T | ABLE | | in the presence | |
| VIII. COMPTICTIVE INDEE | | | | of | |
| | | | | | |

(UN-SUPERVISED)

| Methods | Advantage | Disadvantage |
|--------------|-----------------|------------------|
| K-means | 1. Simple | 1. Requires |
| Clustering | clustering | number of |
| | approach. | cluster in |
| | 2. Efficient. | advance. |
| | 3. Less complex | 2. Problem with |
| | method. | handling |
| | | categorical |
| | | attributes. |
| | | 3. Not discover |
| | | the cluster with |
| | | non-convex |
| | | shape. |
| | | 4. Result varies |
| | | in the presence |
| | | of |
| | | outlier. |
| Hierarchical | 1. Easy to | 1. Have cubic |
| Clustering | implement. | time complexity |
| | 2. Having good | in |
| | visualization | many cases so it |
| | capability. | is slower. |
| | 3. There is no | 2. Decision |
| | need to specify | regarding |

IX. CONCLUSION

noise.

Thus, this paper provides complete survey for medical data mining techniques, Classification methods, clustering and pattern recognition. In this paper we have studied disadvantages and advantages of all methods and algorithm involved in the field of medical data mining. Classification methods mostly categorized into supervised and semi-supervised learning classification, labeled data classification also called statistical data classification. Cluster analysis used for unlabeled data, cluster analysis also called as un-supervised learning. Cluster analysis contains different types of methods, to handle Spherical and Arbitrary type data problems.

Pattern recognition is the process of extracting useful features and generates knowledge using classification and cluster analysis. The Second main use of pattern recognition provide reverse process of predicting given data point using specific classification or cluster analysis. This paper shows all about machine learning approach to medical data, machine learning is an broad domain which is include data classification, cluster analysis and pattern recognition. This paper also state that which type of algorithm suitable for specific data type such as statistical, spherical and arbitrary.

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